Three Essays on Customer Experience Dynamics

By

Hsiu-Yu Hung

A thesis submitted in partial fulfilment of the requirements

for the degree of Doctor of Philosophy

in Business and Management

University of Warwick, Warwick Business School

June 2020

Contents

Tables

Figures

Acknowledgments

Firstly, I would like to express my sincere gratitude to my supervisors, Prof. Nick Lee and Associate Prof. Yansong Hu, for their continuous support and guidance regarding my Ph.D. project and related research, for their inspiration, motivation, patience, and wisdom. Their guidance helped me throughout my research and writing of this thesis. I was extremely fortunate to have them as my supervisors throughout my Ph.D. journey in the UK.

Besides my supervisors, I would like to thank my annual review panels: Prof. Emma Macdonald, Prof. Johannes Habel, and Assistant Prof. Iman Ahmadi. I am very grateful for their comments and encouragement to widen my research from various perspectives. I would like to express my sincerest gratitude to the outstanding VIVA examiners: Prof. John Rudd and Prof. Mirella Kleijnen. I very much appreciated their insightful questions that enriched as well as completed this Ph.D. thesis.

Finally, I would like to say something to my father: “Daddy, I dedicate this book to you for your unconditional love and my endless remembrance.”

（謹以此書獻給我最摯愛的爸爸）

Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy in Business and Management. This thesis has been composed by myself and has not been submitted in any previous application for any degree at any other university. I confirm that the work presented was carried out by the author.

Summary of Abstract

This thesis focuses on unveiling the dynamic nature of the customer experience trajectory and forming a theory of customer experience management from a dynamic perspective through undertaking three studies. Chapter 1 is an introductory chapter, aiming to provide a roadmap of this thesis and indicating the research motivation and major research question of each study. Chapter 2 is a basic literature review, exploring what we know from the current literature and identifying the knowledge gaps to which we can contribute in the realms of customer experience, customer experience trajectory, and customer experience management. Chapters 3-5 are three empirical studies. Chapter 3 focuses on individual customers' perspectives to understand the evolution of their experience trajectories. Chapter 3 proposes a customer experience trajectory (CET) research framework and explores the co-evolutionary phenomenon between customer experience dynamics and customer behavior dynamics. Chapter 4 focuses on the firm's perspective to disclose firms' dynamic trajectories of their customer experience performance through a value co-creation theoretical lens. Chapter 5 focuses on both firms and customers' perspectives and proposes a research framework to depict the dynamic interactions between experience receivers and experience providers. These three studies exploit the advantages of using unstructured textual data drawn from three different well-known online travel-related platforms, including Airbnb (for Chapter 3), booking.com (for Chapter 4), and TripAdvisor (for Chapter 5). Chapter 6 provides a summary of the conclusions. The final chapter discusses the results of the preceding chapters and implications for theory development and managerial tenets provision.

Chapter 1: General Introduction

Things have never been more like they are today in history.

- **Dwight D. Eisenhower**

Last year, each of our 10 million customers came in contact with approximately 5 SAS employees, and each of this contact lasted an average of 15 seconds each time. Thus, SAS is created 50 million times a year, 15 seconds at a time. These 50 million "moments of truth" are the moments that ultimately determine whether SAS will succeed or fail as a business.

- **Jan Carlzon (former president of the airline SAS)**

1.1 Research Motivation

Customer Experience (CX) is a concept that is unavoidable in contemporary marketing strategies, to the point that seemingly all products and services are now sold as an "experience." An examination of Google shows that, over the past decade, there has been a dramatically increasing worldwide pattern of searches for "customer experience" and "customer experience management" (see **Figure 1.1**).

Figure 1.1 Google Trend of Customer Experience (Management) from 2010 to 2019

Furthermore, a LinkedIn job search indicates that more than 1,032,000 professionals in the US, 161,000 professionals in the UK, and 7,000 jobs available in China are associated with terms such as customer experience specialist, head of customer experience, customer experience manager, or customer experience coordinator. These phenomena indicate that firms compete on experience, customers search for experience, and markets are transformed by experience. The importance of providing a superior experience is due to its relevance to customer loyalty and a firm's financial performance. By delivering the desired customer experience, companies can acquire new customers, retain their current clientele, and gain the benefits of brand equity, sales income, stock performance, and competitive advantages. However, a report conducted by Salesforce (2019) found that, of the 4,100 plus marketers surveyed, less than half (49%) of them believe that they provide an experience that is aligned with what their customers expect. This is quite troubling for firms, given that Newell-Legner's report (2019) states that it takes 12 positive experiences for firms to make up for one negative experience.

Setting aside the internal challenges, firms face external challenges from both their customers and their business counterparts. First, a steadily increasing number of consumers view the majority of marketing campaigns with uninterest or skepticism. Consumers are increasingly aware of firms' intended aims and are becoming critical and emancipated observers, rather than receptive targets. Thus, with this consumer mindset, it is harder for marketers to motivate consumers to invest their scarce resources (time/money) in a specific product or service. The second external challenge exists in today's business environment, with its myriad of experience providers and touchpoints (Lemon & Verhoef, 2016; Marriott & Williams, 2018). For example, to complete a single purchase, customers nowadays use multiple channels. They may try out a product in a physical store while simultaneously using their phone or laptop to go online to compare prices, check online reviews, or even place an online order. Customers who did not complete their purchase in store may order similar products using other channels offered by competitors. The challenge reflects the business phenomenon whereby firms are confronted with accelerating media and channel fragmentation (Brynjolfsson et al., 2013; Verhoef, Kannan, & Inman, 2015), customer-to-customer interactions through social media (Leeflang et al., 2013; Libai et al., 2010), and the influences on CX from peer customers, resulting in firms' reduced control of the CX (e.g., Brynjolfsson et al., 2013; Rapp et al., 2015). Thus, CX has become increasingly complex for firms to manage, and it is much harder for them to control the experience of each customer (e.g., Edelman & Singer, 2015; Rawson, Duncan, & Jones, 2013).

In academia, the concept of customer experience is not new. It first appeared in the seminal work of Holbrook and Hirschman (1982) who recognized the important experiential aspects of consumption and constructed a paradigm to contrast the prevailing information processing model with an experiential view that focuses on the symbolic, hedonic, and aesthetic nature of consumption. Holbrook and Hirschman (1982) opened up the path to other outstanding CX scholars. For example, Arnould and Price (1993) found that out-of-the-ordinary experiences impose a boundary condition upon the traditional confirmation-disconfirmation theory of how consumers assess experiences. Schmitt introduced experiential marketing in 1999. Later, Pine and Gilmore (1999), as well as Schmitt (2003), identified customer experience as the next competitive marketing arena and the basis upon which a firm's activities would be organized, in a description of the paradigm of the experience economy in contemporary societies. Consistent with Prahald and Ramaswamy (2004)'s value co-creation perspective, Vargo and Lusch (2004) proposed the service dominant logic and argued that the co-creation of experiences forms the basis of consumer value and that value is always uniquely and experientially determined by the consumers. The key message of their proposition is that all market offerings, services provision, goods, or value propositions are perceived and integrated differently by each unique individual and, thus, value is also uniquely determined and assigned by individual customers. Running parallel to the value co-creation perspective, another dialogical perspective was proposed by Ballantyne and Varey (2006). They posited that firm-customer communication is related to learning and occurs in a many-to-many conversation and interaction, which is not always mediated by the focal firm. Their perspective broadens the dominant framework of marketing communication being directly controlled by firms, into one through which both buyers and suppliers make their value propositions. It is clear that these three strands of customer experience, value co-creation, and many-to-many interactions, are mutually intertwined. In 2009, Verhoef et al. identified the holistic nature of CX in their exploration of the depth and length of customer experience in the context of retail contexts. Other CX contributions that focus on its conceptual investigation include Schmitt (2011), De Keyser et al. (2015), Lemon and Verhoef (2016), and Gahler et al. (2019). For example, Lemon and Verhoef (2016) defined CX as a "multidimensional construct focusing on a customer's cognitive, emotional, behavioral, sensorial, and social responses to a firm's offerings during the customer's entire purchase journey." Gahler et al. (2019) defined CX as "the customer's subjective state during the interaction with an experience provider that holistically evokes affective, cognitive, physical, relational, sensorial, and symbolic response." To summarize, previous CX scholars characterize customer experience as multidimensional, subjective, and holistic. Their definitions of the CX concept encapsulate it as the subjective states of focal customers during their interactions with a/multiple experience provider(s), which holistically evoke their multidimensional responses throughout their consumption journeys. Recently, the prevalent conceptual approaches to CX have emphasized that the CX construct comprises customers' experiences with different kinds of experience providers (e.g., products, brand, firms, personnel, other customers) at different touchpoints (e.g., online websites, advertisements, offline stores, mobile apps, social media, brand communities) and different consumption stages (i.e., pre-purchase, purchase, post-purchase). Such complexity of conceptualization, involving multiple providers, touchpoints, channels, and time-points, reflects the dynamic nature of CX and makes the undertaking of empirical work challenging for CX scholars (Gahler et al., 2019).

Although the CX empirical literature has developed since the introduction of the CX concept, most existing CX empirical research concentrates on the measurement of CX (e.g., Arnould & Price, 1993; Bleier et al., 2019; Brakus et al., 2009; Gahler et al., 2019; Klaus & Maklan, 2013; Klaus, 2015; Lin et al., 2008; Maklan & Klaus, 2011; Schouten et al., 2007; Verleye, 2015), its antecedents (e.g., Bolton, 2016; Klaus & Maklan, 2012; Puccinelli et al., 2009; Swaid & Wigand, 2009), and its consequences (Dick & Basu, 1994; Klaus & Maklan, 2012). Research is limited to specific domains such as brand experience (Barkus, 2009; Dennis et al., 2013; Gentile et al., 2007; Schouten et al., 2007), online experience (Bleier et al., 2019; Hoffman & Novak, 2018; Novak & Hoffman, 2019), product experience (Hoch, 2002; Jiang & Benbasat, 2004), service experience (Edvardsson et al., 2005; Klaus & Maklan, 2013; Mende et al., 2018; Van Vaerenbergh et al., 2019; Voorhees et al., 2017), or retail/shopping experience (Bagdare & Jain, 2013; Frank et al., 2014; Kim et al., 2013; Massara et al., 2014). While the abovementioned empirical research has advanced our understanding of how to manage CX, it addresses the customer experience in a relatively static way. This stands in contrast to the conceptual research that views CX as a dynamic process or as a customer's journey with a firm over time (Lemon & Verhoef, 2016). That is, although previous scholars concur that the CX concept can be best understood through the perspective of the customer journey or dynamic process (e.g., Bonchek & France, 2014; Edelman & Singer, 2015; Lemon & Verhoef, 2016). little is known about how to empirically capture the evolution of customers' perceived experiences throughout their consumption lifecycle (i.e., the stages of acquisition, growth, retention, and win-back) or across customers' repeated journeys with the firm.

Apart from a solitary research stream, researchers have empirically examined the dynamics of CX from the multiple-touchpoints perspective. Touchpoints are viewed as one of the key concepts in the CX journey and constitute the major designable building blocks in the service provision context (Edelman & Singer, 2015; Halvorsrud, Kvale & Følstad, 2016). Research typically defines touchpoints in one of three ways. The first approach describes a touchpoint as an "interactive event" that takes place between the experience provider and its customers (Patrício, Fisk, Cunha, & Constantine, 2011; Zomerdijk & Voss, 2010; 2011). A second definition describes the touchpoint as an "interface" that mediates the interaction between the experience providers and the customer (e.g., Clatworthy, 2011; Secomandi & Snelders, 2011). The third approach integrates the “interface” with the “event” definition so that the definition of a touchpoint is an “instance of communication between a customer and an experience provider” which is “carried or mediated through a channel” (Halvorsrud et al., 2016).

In addition to the different perspectives for conceptualizing the meaning of touchpoints, several studies have identified different “categories” of touchpoint and how they might be managed throughout the consumption journey in order to deliver superior experiences (e.g., Anderl et al., 2016; Baxendale et al., 2015; De Hann et al., 2016). For example, Lemon and Verhoef (2016) identified four categories of CX touchpoints and argued that customers interact with each of these touchpoint categories at each stage of the experience, depending on the nature of the product/service or the customer’s own journey. Moreover, this research stream also recognizes the impact of the broader external contexts, such as political, environmental, economic, social, or technological factors (e.g., Fornell et al., 2010; Gijsenberg et al., 2015; Verhoef et al., 2009), and how these externalities affect specific touchpoints, thereby contributing to the overall CX (e.g., Hunneman et al., 2015; Ou et al., 2014). This research stream provides firms with an understanding of not only the potential leverage points in the CX but also the customers’ dynamic external environments, which can influence/shape the formation of CXs.

- In summary, the existing empirical works on CX have explored the measurement of CX from a multidimensional view; they examine the antecedents and consequences of CX in a relatively static way, and focus on managing CX through the multiple touchpoints/omnichannel perspective. However, given the relatively nascent state of the CX literature, we argue that there is currently very little empirical work that directly delineates and examines the dynamic nature of the CX, or explores how to manage it dynamically, by reference to its dynamic nature and conceptualization. Drawing on previous scholars' contributions (e.g., De Keyser et al., 2015; Gahler et al., 2019; Homburg et al., 2015; Lemon & Verhoef, 2016; Verhoef, Kooge, & Walk, 2016), we define CX as a customer's subjective response during the dynamic encounters/interactions with experience providers, including but not limited to firms, firms' partners, personnel, brands, products, services, or technology, that holistically evoke the customer's multidimensional responses during the CX journey. Further, the CX definition, from the perspective of the focal customer's CX journey, should be understood as an iterative and dynamic process, built up through multiple touchpoints, flowing across multiple stages, and incorporating past/previous CXs as well as external factors. To bridge the dynamic gap between conceptualization and its empirical delivery as discussed above, we aim to extend our understanding of the dynamics of CX by studying it from the perspectives of both the experience providers and the experience receivers since it is co-created by both parties. We also intend to identify the key "changing/evolving" aspects or elements that occur throughout the CX journey, which we regard as the underpinnings for managing CX dynamically. Finally, Kranzbühler, Kleijnen and Morgan (2018) call for future research based on the potential for synergies through connecting the firm perspective with the creation of CXs (CX providers) and the customer perspective with the perception of CX (CX receivers). This thesis thus responds to their call and aligns both perspectives, offering an extended tripartite view, including (1) from the customer's perspective (in study 1), (2) from the firm's perspective (in study 2) and (3) from both the customer and the firm's perspectives (in study 3) to shed light on the interactions between firms and customers.

1.2 The Research Objectives and Major Research Questions

This dissertation aims to empirically disentangle the dynamic nature of the customer experience by developing a stronger understanding, reinforced by empirical evidence, of the dynamics of CX and its relationship with complex customer behaviors.

We do this by conducting three studies in the context of the hospitality industry as follows: (1) from the perspective of the customers/experience receivers; (2) from the perspective of the firms/experience providers; and (3) integrating the perspectives of customers and firms, to increase our understanding of the dynamics of the customer experience. Following the sequences of research foci from the individual perspective in study 1 to the firm's perspective in study 2 and ending with the customer-firm's interactive perspective in study 3, we can portray a complete picture to depict customer experience. Specifically, the goal of disentangling the "dynamics of customer experience" involves understanding the "co-evolution dynamics" between CX and customer rating behavior (study 1), the firms' CX "performance dynamics" (study 2), and the "interaction dynamics" between customers and firms (study 3). Based on the empirical results of these studies, we develop effective CX managerial strategies that correspond to CX's dynamic nature.

1.2.1 Agenda and Research Questions of Study 1

Firms seek strategies to increase customer retention and avoid customer churn since the cost of customer acquisition is far higher than that of retention and a small increase in retention can drive significant profit increases (Gupta & Lehmann, 2003; Pfeifer & Farris, 2004; Reichheld & Sasser, 1990). However, the easy assumption that repeat customers are satisfied customers may lead to a misunderstanding of their experience trajectories and this raises an important question: are the CXs of repeat customers always in a “static, satisfying” state? That is, will the CX trajectories of repeat customers always remain constant? If not, will the repeat customers have fixed perceptions and exhibit consistent behavior throughout their CX trajectories? For marketing practitioners, the consequence of this misunderstanding means that a piece is missing from the overall picture of CX management regarding repeat customer retention. Thus, it is vital to identify repeat customers’ trajectories via the exploration of a series of repeat patronages with regard to a specific experience provider.

Although the research on customer dynamics has investigated customer retention and churning dynamics (Fader & Hardie, 2010), few customer dynamics studies have empirically examined repeat customers’ experience dynamics and the dynamic interactions between repeat customers’ experiences and their preferential behaviors. In study 1 we propose a research framework, namely the customer experience trajectory (CET), which focuses on existing customers’ repeat patronages. The CET framework argues that there is a co-evolutionary phenomenon between customer experience dynamics and customer behavior dynamics, which means that both the customer experience and customer behaviors change over time. We define the repeat customers’ experience trajectories as occurring as customers repeatedly interact with/encounter the same experience providers, whereby their previous experiences influence their current and future experiences.

In this study, we introduce the concept of the "CX performance state" for the CET research framework. A "CX performance state" is defined as the consequences/performance of perceived CXs by the focal customers. Thus, a CX performance state is a perceived experience performance state at the individual level, which is expressed by a combination of repeat customers' behavioral performance at different levels; the behavioral performance includes revisit intention, referral intention, compliments, and complaints. In this research framework, we propose two mechanisms that will influence the migration of the focal customers' CX performance states: (1) the different dimensions of perceived CXs; and (2) managerial-related actions.

Concerning the first migration mechanism, we investigate the dynamic impacts of the multidimensions of CX on the evolution/change of repeat customers' CX performance states, based on the premise that repeat customers may not always remain static. Regarding the second mechanism, we then investigate the effectiveness of various real-world management strategies to identify how different managerial variables vary in terms of their effectiveness for migrating repeat customers throughout their CX performance states and enhancing the preferred customer behavioral performances. To examine the CET framework, we address the following research questions:

(1) How do repeat customers' experience trajectories evolve over time and can the customers be segmented into different groups with different evolutions of CX performance states?

(2) Which migration mechanisms influence the transition across CX performance states? How can experience providers decompose the short- and long-term effectiveness of these migration mechanisms?

(3) How will different segments of repeat customers respond to migration mechanisms as they transition across their CX performance states?

1.2.2 Agenda and Research Questions of Study 2

Study 1 focuses on individuals; study 2 focuses on firms. That is, study 1 focuses on the dynamics of repeat customers' CET states, defined as the perceived CX performance at the individual level. In study 2, the research focus is on firms' CX performance and the dynamics of firms' CX performance states, defined as the CX performance at firm level, as collectively perceived by the firm's clientele. Study 2 sheds light on how to design effective customer experience management strategies throughout the firm's trajectory of its CX performance. Although CX management is among the most promising marketing approaches in the consumer industries, the extant research is insufficient to productively understand the dynamic effectiveness of CX management strategies. Using our proposed framework, which is the firm's trajectory of CX performance, we argue that experience providers migrate through different CX performance states over time, and that managerial strategies have varying degrees of effectiveness throughout the firm's trajectory of CX performance. The CX performance states can be presented as levels, from low to high, calculated by reference to the customers' numerical rating scores and the combinations of different dimensions of CXs as perceived by customers. In the research framework, the objective is to identify the best combination of effective strategies, given the CX performance states of the focal firm.

But how can managers design effective CX management strategies? Relying on the rationale that experience is co-created between experience providers and receivers, particularly in the service sector, we thus draw on the value co-creation perspective (McColl-Kennedy et al., 2012; McColl-Kennedy et al., 2017; McColl-Kennedy et al., 2019; Ordenes et al., 2014) to propose migration mechanisms that will dynamically influence the evolution of a firm's trajectory of CX performance. The proposed mechanisms parsimoniously capture the transitions among firms' CX performance states using four value co-creation elements: (1) Activities; (2) Resources; (3) Contexts; and (4) Interactions, that together make up the ARCI model. We tailor different aspects of elements in the ARCI model to develop two migration mechanisms: a positive mechanism for upward migration across the CX performance states and a negative mechanism for downward migration among the CX performance states. This research aims to answer the following research questions:

(1) How many latent states of CX performance can be identified at the firm's level?

(2) How does the trajectory of firms' CX performance evolve during the research time frame?

(3) How do the positive and negative migration mechanisms composed of the ARCI components influence the transition across different states of CX performance? That is, given a firm's current CX performance state, what is the most effective strategy/element for migrating it to a higher performance state or preventing it from moving to a lower one?

Here, we differentiate the migration mechanisms proposed in our first two studies. The major goal of the migration mechanism in study 2 is to help firms develop theoretically-solid tactics to dynamically manage customer experiences. In contrast, the objective of the migration mechanisms in study 1 is to offer a deeper understanding regarding the “dynamic phenomenon” of individual customers’ CX trajectories. Study 1 focuses on repeat customers’ CX performance states at the individual level. Thus, the major migration mechanisms are proposed at the same (individual) level, examining the dynamic influences of perceived experience by focal customers on the transitions among their CX performance states.

Study 2 sheds light on experience providers’ CX performance states at the firm’s level. Hence, the migration mechanism in study 2 is proposed from a standpoint that can be managed, designed, or at least partially controlled by firms. In study 2, we leverage the value co-creation perspective that envisages the delivery of experience as co-created by firms and customers. Extending Prahalad and Ramaswamy (2004), we depict the value of co-creation as a joint initiative through which experience providers (firms) and experience receivers (consumers) together create the experience. In the co-creation process, value is created reciprocally for both consumers and firms, who engage in the process by interacting and exchanging their “resources.” These “interactions” take place in distinct “contexts” in which customers and firms provide their own “resources,” integrate the resources provided by the other party, and develop experiences through the resource integration process. Furthermore, drawing upon the service-dominant logic form Vargo and Lusch (2004), we assert that the value of the resources is co-created within the customer experience. Therefore, the knowledge, skills, and capabilities of employees who are in contact with the customers are the primary determinants of the ability of the focal firm to co-create and share value with its actual and potential customers (e.g., Maglio et al., 2009). In study 2, we draw on two theoretical underpinnings, value co-creation and the service dominant logic, to propose the ARCI migration mechanism, comprised of firms' and customers' activities, resources, service contexts, and interactions at the collective level.

1.2.3 Agenda and Research Questions of Study 3

In study 3, we integrate perspectives from both the experience providers and experience receivers. This study elucidates the dynamic interactions between customer reviews (CRs) regarding their received services or perceived experiences, and firms' managerial responses (MRs) to these CRs. Based on the phenomenon that online CRs have gained overwhelming credibility in the eyes of consumers and thus are an essential component of the consumer decision-making process (Chevalier & Mayzlin, 2006; Luca, 2011), it is crucial for firms to gain an understanding of their clients' CXs as expressed via verbatim comments and recognize that the practice of publicly responding to consumers is a valid CX management strategy. Through understanding the dynamic effects of MRs on future CRs, firms might achieve their managerial objectives by highlighting positive comments (thereby acquiring potential customers and retaining current clients) and by mitigating the impact of negative comments (thereby preventing customer churn or the spread of negative eWOM).

However, recent research on online reviews indicates that the use of MRs by firms remains limited (e.g., Chen, Gu, Ye, & Zhu, 2019; Lappas et al., 2016; Levy et al., 2013); more specifically, more than half of the firms surveyed report that their preparedness for online negative WOM is below average (e.g. ethical Corporation, 2012; Herhausen et al., 2019). In addition, previous MR research has not yet reached a consensus regarding the impacts, underlying mechanisms, or pros and cons of MRs on future customer reviews and business performance (e.g., Chen et al., 2019; Chevalier et al., 2018; Herhausen et al., 2019; Kumar et al., 2018; Proserpio & Zervas, 2017). To address these knowledge gaps, this thesis leverages the concept of the "echoverse" (Hewett et al., 2016) to portray a communication environment in which the actors (firms and customers) contribute and are influenced by each other, reflecting dynamic firm-customer interactions. We propose an online "CR-MR Echoverse" framework to investigate the dynamics among online CRs and online MRs. We also use the "CR-MR Echoverse" to depict the online communication environments shared by the experience providers and receivers. The building blocks of the CR-MR Echoverse include distinct

CR components and MR components, which together comprise a reverberation system that portrays the spillover effects of MR components on future CR components, and the herding effects among CR components. We introduce several theories to unravel the critical components of MRs and CRs, including emotion regulation, cognitive appraisal, affective infusion, similarity perceptions, service recovery, and herding behaviors. This thesis further draws on two practical perspectives, customers' emotion regulation and rating behavior management, to tailor the best MR strategies in online rating contexts. Specifically, we ask the following research questions in order to generate a complete theory of the MR-CR Dynamics to contribute to the CX management literature:

(1) What are the major elements of online MRs and online CRs, respectively, that firms should strive to influence?

(2) Given the different elements of MRs, what are the dynamic spillover effects of online MRs on the distinct elements of later CRs? What are the dynamic herding behaviors among CRs?

(3) How might managers model the above results to label MR strategies that seek to promote positive CRs or suppress negative ones as dynamic online MR strategies?

Finally, we summarize the research focus and major goals of these studies. **Table 1.1** thus provides an overview of the three studies that form this Ph.D. dissertation.

Table 1.1 Overview of the Three Studies

Title	Study 1	Study 2	Study 3
Research Focus & Perspective of Each Study	From the individual customers' perspective	From the firm's perspective	From both the customers' and firm's perspectives
	Focus on repeat customers' experience trajectories	Shed light on the firm's CX performance trajectory	Emphasize the dynamic customer-firm interactions
Research Goals of Each Study	**Delineate** 1. The dynamic nature of the customer experience and its influences on the experience trajectory 2. The co-evolution phenomenon between customer experience dynamics and customer behavioral dynamics 3. Effective triggers that improve the customer experience trajectory	**Disentangle** 1. The trajectory of firms' customer experience performance 2. The design of positive and negative mechanisms to influence the firm's CX performance from the value co-creation perspective 3. The dynamic effects of the proposed CX management mechanisms	**Quantify** 1. The dynamic effects between customer-firm interactions throughout the firm's CX performance trajectory 2. The herding effects among different components of CRs 3. The spillover effects of the firm's managerial responses on future customers' CRs
Common Goal among Three Studies	1. Capture CX trajectories (from three aspects) to portray a comprehensive paradigm of CX dynamics for theoretical contribution **2.** Design dynamic CXM strategies for practical implications		

Chapter 2: Basic Literature Review

This chapter reviews the existing literature on customer experience, customer experience dynamics, and customer experience management. It aims to provide the background to the three papers in Chapters 3-5 that comprise the substantive work of this Ph.D. thesis.

2.1 Customer Experience

Customer experience (CX) has become a hot topic in the business world. Although it is often suggested to be a company's first concern (Meyer & Schwager, 2007), CX is also a relatively complex construct that can easily be confused with other concepts in marketing, such as customer engagement or customer relationship management (Homburg et al., 2017; Lemon & Verhoef, 2016). In order that CX may be understood, section 2.1.1 presents a detailed literature review that defines the concept of CX as well as its multidimensional nature. Moreover, to gain further insights into the concept of CX, it is useful to differentiate it from other customer-focused constructs, and this is done in section 2.1.2.

2.1.1 The Definition and Nature of CX

In order to understand CX, it is useful to explore its origins, i.e., the history of the phenomenon. The importance of customer experience as the driver of consumption was mentioned early on in the economic literature. Parsons (1934) suggests that product utility function alone is insufficient to explain consumer behavior. He posits that consumers' choices are driven by their personal value systems, which lead them to determine whether an experience is desirable or not. Therefore, customers buy goods to create desired experiences (Keynes, 1936). Later, Abbott (1955) focused on the notion that what consumers really desire is not so much a product as a satisfying experience. Despite this early identification by the economic literature of the importance of the customer experience as a sufficient choice criterion, Ajzen and Fishbein (1977) focused on explaining customer behaviors as a rational cognitive process, linking customer actions with the paradigm of cognition, affect, and behavior (the CAB Model). CAB research suggests that customers are involved in a rational assessment of their past, present, and imagined future experiences, and use their cognitive information to determine their behavioral intentions (see, for example, Holbrook, 1986; Schiffman & Kanuk, 1997; Solomon, 1997).

However, in contrast to the CAB research stream that focuses on consumers' cognitive/rational process, experiential researchers (e.g., Arnould & Price, 1993; Holbrook & Hirshman, 1982; Schmitt, 2001) challenge the model's emphasis and suggest that emotions play a critical role in consumer behavior. For example, Hirschman and Holbrook (1982) encourage a broader view that recognizes the emotional aspects of decision-making and experience. Building upon emotional factors as a cornerstone, two research streams emerge: extraordinary experiences (Schouten, 2007) and the overall assessment of customer experience (Klaus & Maklan, 2011; Verhoef, 2009). Researchers later progress to exploring various perspectives that put forward explanations of how customer experience arises and evolves during the interactions between customers and the firm, channels, products, services, employees, and other consumers (e.g., Schmitt, 2003). During the period from the late 1990s to the early years of the 21st century, scholars considered CX to be an aggregation of emotional and mental feeling (Carbone & Haeckel, 1994; Edvardsson et al., 2005; Padgett & Allen, 1997; Sandström et al., 2008) that is subjectively perceived by customers (Meyer & Schwager, 2007) during their interaction, encounter, or progress with a product and/or service consumption (Carbone & Haeckel, 1994; Edvardsson et al., 2005; Gupta & Vajic, 1999; Padgett & Allen, 1997). For example, Pine and Gilmore (1998, p. 3) conceptualized the idea of "experiences" as distinct from goods and services, noting that a consumer purchases an experience to "spend time enjoying a series of memorable events that a company stages…to engage him in an inherently personal way." After this, other scholars developed a broader view of the concept of CX. For example, Schmitt, Brakus, and Zarantonello (2015) suggest that every service exchange leads to customer experience, regardless of its nature and form. This broader perspective considers CX to be holistic in nature, incorporating the customer's cognitive, emotional, sensory, and spiritual responses to her every interaction with a firm (e.g., Bolton et al., 2014; Gentile, Spiller, & Noci, 2007; Lemke, Clark, & Wilson, 2011; Verhoef et al., 2009). The current consensus adopts this broad view of CX, with Gahler et al. (2019) characterizing CX from the customer's perspective as a subjective and holistic phenomenon. **Table 2.1** lists, in chronological order, the major studies that contribute to the CX concept.

Table 2.1 Selective Research Focusing on the Customer Experience

Authors (Year)	Theoretical Perspective	The focus of CX Investigation
Keynes (1936) Parsons (1934)	Economic theory	Goods are a means to an end utility, having no value in and of themselves.
Fishbein and Ajzen (1976), Sheppard et al. (1988)	Psychological theory	Consumers are rational information processors, able to assess the consequences of their decisions.
Hirschmann and Holbrook (1982)	CB theories	Value is generated by experiences, not the acquisition of goods; people consume experiences using emotional and hedonic faculties.
Hui and Bateson 1991	CB theories	Perceived control in service experiences.
Arnould and Price (1993)	CB theories	Out-of-the-ordinary experiences.
Shouten and McAlexander (1995) McAlexander (2002)	Brand communities	Contributions to the impact of shared experience on consumer experience and brand engagement.
Winsted (1997)	CB theories, culture theory	Service experiences in different cultures.
Pine and Gilmore (1998)	CB theories, flow model	Experience economy and different CX types.
Novak et al. (2000)	CB theories, flow model	Flow model of online experiences.
Hoch (2002)	CB theories, philosophy	The seductive character of product experiences.
Schmitt (2003)	Practitioner	Customer experience as the next competitive marketing arena and the basis for organizing a firm's activities.
Prahalad and Ramaswamy (2004)	Service marketing	Co-creation of experience is the basis of consumer value.
Gentile (2007)	CB theories	Multidimensional CX and leveraging options.
Schouten et al. (2007)	CB theories	Transcendent CX in brand communities.

Authors (Year)	Theoretical Perspective	The focus of CX Investigation
Vargo and Lusch (2008)	Service-Dominant (S-D) logic	The notion of experiential value in use.
Brakus et al. (2009)	CB theories, philosophy	Scale development of brand experiences.
Grewal et al. (2009)	CB theories	Macro and market factors that shape CX.
Puccinelli et al. (2009)	CB theories	CX in various stages of the decision process.
Verhoef (2009)	CB theories	Identifies the depth and length of consumer experience in the context of retail.
Lemke et al. (2011)	CB theories, SD logic	CX quality and effects on relational outcomes.
Schmitt (2011) De Keyser et al. (2015); Homburg et al. (2015); Lemon and Verhoef (2016); Gahler at el. (2019); Kuehnl et al. (2019)	CB theories	CX during a customer's interaction with different kinds of experience providers at different touchpoints and customer journey stages.

This short history of the CX concept's development hints at how the definition of the term has similarly evolved. First, Verhoef et al. (2009) define CX as a multidimensional construct and explicitly state that the CX construct is holistic in nature, involving the customer's cognitive, affective, emotional, social, and physical responses to the experience provider. Similarly, Brakus et al. (2009) convincingly conceptualize the construct as consisting of four separate, albeit related, dimensions: sensory; affective; intellectual; and behavioral. De Keyser et al. (2015) describe CX as comprising the cognitive, emotional, physical, sensorial, spiritual, and social elements that mark the customer's direct or indirect interaction with other market actors. Lemon and Verhoef (2016) conclude that CX is a multidimensional construct that focuses on a customer's cognitive, emotional, behavioral, sensorial, and social responses to a firm's offering during the customer’s entire purchase journey. Gahler et al. (2019) define CX as the customer's subjective state during an interaction with an experience provider that holistically evokes affective, cognitive, physical, relational, sensorial, and symbolic responses. **Table 2.2** summarizes the various conceptualizations of the CX concept’s dimensions by reference to the findings of the key researchers.

Table 2.2 Summary of the Dimensions of the CX Concept according to CX Researchers

Authors (Year)	**Dimensions of CX**								
	Affective	Cognitive	Emotional	Physical	Relational	Sensorial	Symbolic	Social	Spiritual
Bolton et al., 2014		✓	✓			✓		✓	✓
Brakus et al., 2009	✓	✓		✓		✓			
De Keyser et al., 2015		✓	✓	✓		✓		✓	✓
Gahler et al., 2019	✓	✓		✓	✓	✓	✓		
Gentile et al., 2007		✓	✓		✓	✓	✓	✓	✓
Lemke et al., 2011, 2010		✓	✓			✓	✓	✓	✓
Lemon and Verhoef 2016		✓	✓	✓		✓		✓	
Schmitt 1999	✓	✓		✓		✓		✓	
Schmitt 2003		✓	✓	✓		✓		✓	
Schmitt 2011	✓	✓		✓		✓			
Schmitt et al., 2015		✓	✓			✓		✓	✓
Verhoef et al., 2009	✓	✓	✓	✓				✓	

The affective dimension of the CX concept is related to the emotions, feelings, moods that arise during a customer’s interaction with an experience provider (Brakus et al., 2009; Gentile et al., 2007). The cognitive dimension is related to the thoughts, ideas, insights, and learning that arise during a customer’s interaction with an experience provider (Gentile et al., 2007; Schouten et al., 2007). The physical dimension is related to the body movements and physical actions that occur during a customer's interaction with an experience provider (Brakus et al., 2009; Schouten et al., 2007). The relational dimension incorporates the social relationships and feelings of belonging that are created during a customer's interaction with an experience provider (Arnould & Price, 1993; Gentile et al., 2007). The sensory dimension is related to the sights, sounds, physical contact, tastes, and smells that arise during a customer's interaction with an experience provider (Brakus et al., 2009; Schmitt, 1999). Finally, the symbolic dimension is related to the self-affirmation and self-expression that occur during a customer's interaction with an experience provider (Gentile et al., 2007; Lemke et al., 2010). In this thesis, these dimensions are organized into five categories that comprise the CX concept: (1) the cognitive-rational dimension; (2) the affective-emotional dimension; (3) the social-relational dimension; (4) the physical-sensorial dimension; and (5) the symbolic-spiritual dimension.

In addition to this multidimensional aspect of the CX concept, CX may also be related to specific aspects of the offering (e.g., brands) or particular contexts (e.g., online stores) in that it consists of the individual interactions between the firm and its customers at distinct points in the experience; these are called touchpoints (Homburg et al. 2015). CX can be built up through a collection of touchpoints during multiple phases of a customer's decision-process or purchase journey (Puchnelli et al., 2009; Verhoef et al., 2009). In conclusion, there are several elements that characterize the nature of CX concept. That is, CX is (1) subjective and (2) multidimensional, contingent on (3) a variety of customer interactions at different touchpoints that (4) occur as a process throughout the consumption journey. As such, there can be no doubt that developing a clear, holistic definition of the CX concept is challenging.

2.1.2 CX as a Distinct Construct

For an improved understanding of the CX concept, one must define CX in a way that differentiates it from other customer-focused concepts in the marketing realm; these include service quality (Bitner, Ostrom, & Morgan, 2008; Parasuraman, Zeithaml, & Berry, 1988), consumer relationship management (Kumar & Shah, 2009; Reinartz & Kumar, 2000), and consumer engagement (Hollebeek, Glynn, & Brodie, 2014; Libai et al., 2010; Van Doorn et al., 2010). First, service quality and its constituent elements can be considered as the antecedents of CX (Lemon & Verhoef, 2016), in line with earlier research (e.g., Bitner, 1990; 1992; Bitner, Ostrom, & Morgan, 2008; Mittal, Kumar, & Tsiros, 1999). Second, it may be argued that constructs in customer relationship marketing (CRM), such as trust and commitment, are also related to the customer experience and may influence a customer's follow-on experiences (Lemon & Verhoef, 2016). Hence, commitment, as a measure of a customer's connection with a company, would be a consequence of the customer experience. On the other hand, trust, as an overall assessment of a firm's reliability and benevolence, would primarily be considered a related variable that does not directly influence a customer's experience (e.g., Geyskens, Steenkamp, & Kumar, 1998). However, a good customer experience might build trust. Thus, we would argue that service quality can be viewed as an antecedent of CX but that CRM-related constructs (e.g., commitment, trust, brand attachment) are consequential to the CX construct. Third, some may argue that the CX concept is related to the construct of customer engagement. For example, Brodie et al. (2011, p. 260) define customer engagement as "a psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g., a brand) in focal service relationships". Vivek, Beatty, and Morgan (2012, p. 133) provide an extensive review of the engagement literature and define customer engagement as "an individual's participation in a connection with an organization's offerings or organizational activities, which either the customer or the organization initiates". This approach has been extended, especially as the digital and social media revolution has strengthened the importance of customer engagement behavior with customers becoming either active co-producers or destroyers of value for firms (Beckers, Risselada, & Verhoef, 2014; Bolton, 2016; Leeflang et al., 2014; Van Doorn et al., 2010; Verhoef, Reinartz, and Krafft, 2010). Building upon these previous contributions, it is reasonable to argue that customer engagement focuses on the extent to which the customer reaches out to and initiates contact with the firm. As such, these customer engagements constitute “touchpoints” along the customer’s journey and result in cognitive, emotional, behavioral, sensorial, and social responses from the customer. Thus, this thesis proposes that customer engagement operates as the “pre-condition” of CX. That is, customer engagement must occur before a perceived CX can happen. Given that many channels and touchpoints are highly interactive and provide multiple opportunities for customers to engage with a firm, it is essential to consider customer engagement as a critical pre-conditioning determinant for CX development.

2.2 Customer Experience Dynamics

According to the rationale of section 2.1, the CX concept appears to be a dynamic process, i.e., a customer's journey or trajectory with an experience provider over time during the purchase cycle across multiple touchpoints. Indeed, Lemon and Verhoef (2016) view CX from a process perspective, in that it moves from pre-repurchase to purchase to post-purchase, and they consider it to be iterative and dynamic in nature. Moreover, Lemon and Verhoef (2016) propose that this process incorporates past experiences (including previous purchases) as well as external factors that will influence or shape the CX journey/trajectory. In other words, the customer journey is defined as the process across all the stages and touchpoints that the customer traverses with an experience provider, forming the customer experience (Hamilton & Price, 2019). Recent research has underscored the importance of examining the customer journey in order to understand the customer experience. Thus, Lemon and Verhoef (2016) conceptualize CX as a dynamic process; a customer's journey with a firm over time. Mapping the customer journey from the firm's perspective has long been a valuable tool for improving customer experience (Bitner et al., 2008; Dhebar, 2013; Edelman & Singer, 2015; Rawson et al., 2013). Building upon these rationales, understanding CX through the lens of a dynamic journey/process will provide a window into customers' underlying perceptions of their CX, thereby helping firms/managers to interpret and extract information and evaluate their clients' CXs more accurately. This thesis takes the stance that although an individual experience may last only a brief moment, the overall CX must be seen as a dynamic process that involves distinct purchase stages, lifecycles, or touchpoints. Taking a hotel stay as an example, the dynamic process might include an individual's online searching experience, the ordering/payment experience, consumption experience, room service experience, facilities' usage experience, dining experience, check-in/check-out experience, and parking experience, all of which constitute the total hotel stay CX. Thus, CX is subjective, holistic, and multidimensional and should be regarded from a dynamic process perspective. This thesis therefore uses the concept of a journey to depict the dynamic nature of CX. Furthermore, there are several elements incorporated in the concept of the customer journey, namely (1) the purchase cycle, (2) multiple touchpoints, and (3) external influences. **Table 2.3** summarizes the literature concerning the three abovementioned components as they relate to the concept of consumer journey.

Table 2.3 Review of the Previous Research on the Three Components of the Customer Journey

Major Components	Subcomponents	Authors (Year)	Key Findings
Purchase Cycle	**Pre-purchase**	Hoyer 1984; Pieters et al. 1995	Firms should seek to understand both the firm and customer perspectives, identifying specific touchpoints and trigger points throughout the purchase journey.
	Purchase	Kotler and Keller 2015 Berry et al. 2002 Baker et al. 2002 Ofir and Simonson 2007 Broniarczyk et al. 1998 Iyengar and Lepper 2000 Elberse 2010 Manchanda et al. 2006	
	Post-purchase	Holbrook and Hirschman 1982 Van Doorn et al. 2010 Court et al. 2009	
Multiple Touchpoints	**Brand-owned**	Hanssens 2015 Baxendale et al. 2015 Hanssens et al. 2014 De Haan et al. 2016; Skiera and Nabout 2013	These touchpoints are the customer interactions during the experience that are designed and managed by the firms and are under their control. Most studies research the effects of brand-owned touchpoints on sales, market shares, satisfaction, customer attitudes, and preferences.
	Partner-owned	Ataman et al. 2008	These touchpoints are the customer

Major Components	Subcomponents	Authors (Year)	Key Findings
		Dorotic et al. 2011 Lemon and Van Wangenheim 2009	interactions during the experience that are jointly designed, managed, or controlled by the firm and one or more of its partners. Partners may also influence brand-owned touchpoints.
	Customer-owned	Vargo and Lusch 2004 Mogenson 2015	These touchpoints are the customer actions that form part of the overall customer experience but which the firm, its partners, and other actors neither influence nor control.
	Social-owned	Baxendale et al. 2015; Risselada et al. 2014; Lin and Liang 2011; Manchanda et al. 2015; De Vries et al. 2012; Onishi and Manchanda 2012; Pauwels et al. 2016; Chevalier and Mayzlin 2006	These touchpoints recognize the important role played by others, including the influences of peers, extra-role behavior, proximity, social environments, third-party information sources, social media, or reviews, that may influence the CX process.
Dynamic Influences	**Past Experiences;** **Repeat Experience**	Bolton and Lemon 1999 Verhoef et al. 2007; Lervik-Olsen et al. 2015; Rego et al. 2013; Verhoef and Van Doorn 2008	Past experiences at each stage of the customer experience journey may influence the current experience. The underlying mechanism includes the interrelationships between channel attitudes in different purchase phases, expectation formation and stickiness in experience evaluations, and the dynamic effects of CX that occur within customers who themselves change over time.
	Dynamics and Externalities	Verhoef et al. 2009; Fornell et al. 2010; Kumar et al. 2014 Gijsenberg et al. 2015; Hunneman et al. 2015; Ou et al. 2014	The impact of broader externalities on the customer experience, such as external environments, specific external contexts, the state of the economy, major internal events, sector-wide events, or competitor actions. These externalities can affect how specific touchpoints contribute to the overall customer experience.

As shown in **Table 2.3**, the “dynamic nature” or “journey” of CX involves (1) time (e.g., different purchase stages and consumer lifecycles, the influences of previous experiences), (2) place (e.g., myriad touchpoints, omni-channels), and (3) interactions between people/events/environments. The research listed in **Table 2.3** provides an understanding of the customer journey concept by identifying the specific touchpoints that occur throughout the journey, the specific triggers that lead customers to continue/discontinue their journeys, and the touchpoints that firms can influence/manage. This generates an understanding of the dynamic interactions exerted by the external environments, customer-customer interactions, firm-customer interactions, and social influences.

Moreover, from the marketing practitioners' perspective, other practically-oriented/ empirical research has underscored the importance of examining the customer journey (CJ) in order to manage CX. Two major research streams that focus on this topic are (1) customer journey mapping or service blueprinting and (2) the perspectives from multiple channels, mobiles, platforms, or new technology.

Customer Journey Mapping and Service Blueprinting.

Mapping CJs from a firm's perspective has long been a valuable tool for improving CX (e.g., Bitner et al., 2008; Dhebar, 2013; Edelman & Singer, 2015; Rawson et al., 2013). Furthermore, the service blueprinting methodology is leveraged as a customer-focused approach that enables an understanding of how the CJ can help to develop an optimal service design (e.g., Bitner et al., 2008; Sampson, 2012). Nevertheless, theory and research both call for advances in CJ mapping, moving toward a more adaptive and customized mapping process that goes beyond the firm's perspective to incorporate more of the pre- and post-firm components of the CJ (Lemon & Verhoef, 2016; Rosenbaum et al., 2017; Voorhees et al., 2017).

Perspectives of Multichannels, Mobiles, and New Technology. Research on leveraging multiple channels to manage CXs offers insights into analyzing, managing, and influencing the customer journey (e.g., Ansari, Mela, & Neslin, 2008; Bilgicer et al., 2015; De Keyser et al., 2015; Ko, Kim, & Lee, 2009; Leeflang, 2013; Melis et al., 2015; Venkatesan, Kumar, & Ravishanker, 2007; Verhoef et al., 2015; Wang, Malthouse, & Krishnamurthi, 2015). Research on leveraging new technology to improve understanding of CJ introduces many different channels through which consumers can interact with product and service providers, giving consumers considerable control over their interactions with providers (e.g., Barwitz & Maas, 2018; Chheda et al., 2019; Court et al., 2009; Edelman & Singer, 2015; Kannan & Li, 2017; Leeflang et al., 2014). Research on the mobile perspective focuses on the introduction of new mobile channels and touchpoints that prompt switching across channels and add greater complexity to the customer journey (e.g., Brinker, Labaugh, & Paul, 2012; Husson et al., 2014). **Table 2.4** summarizes the literature these research streams on the customer journey.

Table 2.4 Summary of the Research Streams on Understanding the Customer Journey (CJ)

Stream	Focus	Authors (Year)	Major Findings/Contributions
Customer Journey Mapping		Bitner et al. 2008; Dhebar 2013; Edelman and Singer 2015; Rawson et al. 2013; Voorhees et al. 2017; Rosenbaum et al. 2017	A valuable tool for improving CX.
Service Blueprinting	Service blueprinting methodology	Bitner et al. 2008	Leverages knowledge about the customer journey to develop an optimal service design, referring to a customer-focused approach for service innovation and service improvement.
	Process-chain-network analysis	Sampson 2012	Internally-oriented in that it builds employee insights through ideation or brainstorming into the service delivery process and service design.
Multichannel Perspective	The choice of one specific channel	Eastlick and Feinberg 1999; Leeflang et al. 2013	Mainly considers channel choice behavior.
	Online channels	Ansari et al. 2008; Bilgicer et al. 2015; Melis et al. 2015; Venkatesan et al. 2007	Assesses the drivers of online channel use, including sociological and psychological perceived benefits and costs, social influence, marketing mix instruments, past purchase behavior.
	Mobile channel	Ko et al., 2009; Wang et al., 2015; Brinker et al. 2012; Husson et al. 2014; Chaffey 2016; De Hann et al. 2015; Rapp et al. 2015; Verhoef et al. 2007	The introduction of mobile channels and touchpoints will induce more switching across channels and add complexity to the customer journey. It may enhance cross-channel synergies. Mobile channels have specific characteristics that make them more suitable for searching and less suitable for purchasing. The mobile channel also directly interferes with and interacts with other channels.
	Multichannel focus	De Keyser et al. 2015; Konus et al. 2008	Considers the choice of multiple channels across various phases of the customer experience (CX) and identifies specific multichannel usage patterns and multichannel segments.
	Showrooming	Brynjolfsson et al. 2013;	Provides evidence for the presence of the

Stream	Focus	Authors (Year)	Major Findings/Contributions
	Webrooming	Rapp et al. 2015; Verhoef et al. 2007	"research" shopper, a customer who searches on one channel and purchases on another.
	Post-purchase channel	De Keyser et al. 2015; Gensler et al. 2012	Extends the previous stream to post-purchase channels.
	Mechanisms underlying channel choices	Gensler et al. 2012; Konus et al. 2014; Melis et al. 2015; Verhoef 2007	Investigates the mechanisms underlying subsequent channel choices, such as the search and purchase attribute advantages of specific channels, lack of lock-in to the channel, cross-channel synergies, channel inertia, the distinction between the benefits and costs of different channels.
New Technology and Platform Perspective	Evolving technology development and the diffusion of channels	Barwitz and Maas 2018; Chheda et al. 2019; Leeflang et al. 2014; Harmeling et al. 2017	The introduction of different channels through which consumers can interact with providers, giving consumers considerable control over how they interact with providers. The distinction between the benefits and costs of channels (especially online-offline) is shrinking.
Mobile Perspective	The mobile effects	Bart et al. 2014; Brasel and Gips 2015; Chung et al. 2009; Hui et al. 2013; Klesse et al. 2015; Wang et al. 2015	Mobile offers new marketing tactics for firms. There are positive effects of mobile promotions, the adoption of mobile shopping on purchasing behavior as well as of the influence of touchscreens on customer decision-making.

Table 2.4. offers several insights to understanding the customers' choice of touchpoints where multiple touchpoint options exist. Based on the results of the research listed in **Table 2.4**, one can understand customers' channel choice behavior and the drivers of channel choice; specific multichannel usage patterns and multichannel segments can also be identified, as can the mechanisms underlying these channel choices.

The literature review presented in sections 2.1 and 2.2 enables gaps to be identified in the existing CX and CJ literature. First, the existing research is limited to specific experience providers (e.g., only brands), touchpoints (e.g., only online), or customer journey stages (e.g., only post-purchase). Consequently, marketing practitioners are unable to apply the findings to all the different, potential types of interactions between customers and experience providers at different touchpoints and journey stages. In other words, the majority of existing CX literature focuses on specific facets of these phenomena. Second, to the best of the author's knowledge, there is no empirical work that simultaneously investigates the multidimensional, holistic, and dynamic nature of CX in a single study. That is, there is no existing empirical research that examines the dynamic nature of CX from the process/journey view, embracing its multidimensional, holistic nature as well as the interactions and mechanisms that may exert influences on CX dynamics. This thesis aims to address this gap.

2.3 Customer Experience Management (CXM)

Although marketing practitioners have considered CX management (CXM) as one of the most promising marketing approaches in the consumer industries, the notion of CXM is, for academics, less well developed and insufficiently demarcated from other marketing management concepts, such as customer relationship management (e.g., Achrol & Kotler, 2012; Davey, 2012; Payne & Frow, 2005; Webster & Lusch, 2013). As such, it is unsurprising that 93% of more than 200 firms that engage in CXM are dubious about how efficiently it is being deployed (Temkin & Bliss, 2011). Therefore, in section 2.3.1 we review the existing literature on CXM to identify any knowledge gaps. Section 2.4 offers a brief review of the related literature that is intended to close the gaps identified in sections 2.1- 2.3, while building up a general research framework.

2.3.1 The Existing Literature on CX Management and Gap Identification

Schmitt (2003) defines CXM as the process of strategically managing customers' entire experience with a product or company. Homburg et al. (2015) define CXM as comprising the cultural mindset about customer experience, the strategic directions for designing the customer experience, and the firm's capabilities to continually renew the customer experience, all of which contribute to the goals of achieving and sustaining long-term customer loyalty. To define the CXM concept via clarifying what it is not, this thesis draws on the argument of Meyer and Schwager (2007), who differentiate CRM from CXM. Meyer and Schwager (2007) argue that CRM entails knowing one's customers and leveraging that data while the CXM entails knowing how one's customers react and behave in real-time and leveraging that data. Homburg et al. (2015) discuss how CXM differs from CRM in many respects. For example, CRM has a strong value extraction focus whereas CXM emphasizes value creation. Similarly, a number of studies have alluded to CXM as an appropriate approach for implementing an evolving marketing concept (e.g., Achrol & Kotler, 2012; Webster & Lusch, 2013). However, Payne and Frow (2005) consider customer experience management (CXM) and customer relationship management (CRM) to be incorporated in a strategic perspective on CRM, consistent with the firms that consider CXM to be part of advanced CRM (e.g., Davey, 2012). Thus, there exists a knowledge gap in terms of CXM's links to related marketing concepts. **Table 2.5** provides an overview of the main literature with a CXM focus.

Table 2.5 Selective Literature on CX Management (CXM)

Authors (Year)	Theoretical Perspective	CXM Focusing Contribution
Berry et al. 2002	Best practice studies	Experience audit and design as part of CXM.
Smith and Wheeler 2002	Best practice studies	A step-by-step process for managing CX.
Schmitt 2003	Best practice studies in a brand context	A five-step process for managing CX.
Edvardsson et al. 2005	S-D logic	Design of pre-purchase service experience.
Meyer and Schwager 2007	Applied research	Comparison of CXM and CRM.
Zomerdijk and Voss 2010	CB theories; S-D logic	Design of experience-centric services.
Patricio et al. 2011	S-D logic	Multilevel service experience design.
Homburg et al. 2017	Resource-based view; S-D logic	Build up a CXM framework through grounded theory.

As presented in **Table 2.5**, several studies focus on the service context, specifically the development of schemes and methods for service experience design, by drawing on the features of service-dominant (S-D) logic; others provide ad-hoc guidance for CXM that entails strategically managing a customer's entire experience with a product or company. Although Homburg et al. (2017)'s qualitative work discloses a typology of four distinct CXM patterns, there is a lack of empirical research that elaborates on its concrete underpinning theories and investigates its feasibility as a stand-alone concept. Homburg et al., introduce CXM as a higher-order resource of cultural mindsets toward CX strategic directions for designing CXs and a firm's capability for continually renewing CX, but their findings are subject to the interpretation of researchers' coding of qualitative data. Therefore, their conceptualization should be further operationalized by future scholars in order to quantitatively test its effectiveness and generalizability.

Moreover, there are five major research streams in the literature related to the topic of CXM. The first stream relates to service experience design (e.g., Edvardsson et al., 2015; Homburg et al., 2017; Patricio et al., 2011; Zomerdijk & Voss, 2010). The second stream is related to practice-oriented studies, with multiple practice-oriented authors stressing the importance of CXM across customer touchpoints (e.g., Edelman & Singer, 2015; Rawson et al., 2013). The third research stream employs customer journey design or touchpoint design as the means of providing an optimal experience to customers (e.g., Berry et al., 2002; Meuter et al., 2000; Patricio et al., 2008; Smith et al., 1999; Zhu et al., 2013) by, for example, considering how the interactions between the channels affect CX (e.g., Cao & Li, 2015; Falk et al., 2007; Emrich et al., 2015; Emrich & Verhoef, 2015; Herhausen et al., 2015; Neslin et al., 2006). Some research in this stream focuses on how specific touchpoints contribute to the customer experience at different stages (e.g., Baker et al., 2002; Bart et al., 2014; Gomez et al., 2004). The fourth research stream is concerned with leveraging the network view that recognizes the roles of communities, experience networks, service delivery networks, collaborators, and the broader ecosystem in which the experience occurs (e.g., Bodine, 2013; Patricio et al., 2011; Provan & Kenis, 2008; Sampson, 2012; Tax et al., 2013; Teixeira et al., 2012). The fifth stream is related to the internal firm perspective since managing the CX also enables the firm to develop a CX response orientation (e.g., Homburg et al., 2015), or a customer-centric orientation (e.g., Shah et al., 2006), or an interactive customer orientation (Ramani & Kumar, 2008), or specific capabilities such as partner-network capabilities, customer analytics, and multidisciplinary approaches (e.g., Risselada et al., 2016; Homburg et al., 2015). **Table 2.6** presents the main literature on the five research streams related to the CXM topic.

Table 2.6 Summary of the Main Literature on the Research Streams related to CXM

Major Streams	Sub Streams	Authors (year)	Key Findings
Service Experience Design Research	S-D logic in the service context	Berry et al. (2002); Smith and Wheeler (2002); Edvardsson et al. (2005); Meyer and Schwager (2007); Zomerdijk and Voss (2010); Patricio et al. (2011)	Draws on S-D logic to design the schemes and method of service experience, focusing on the service context.
Practice-Oriented Studies	Managerial-oriented; Customer-centric orientation, experience-oriented mindset	Schmitt (2003); Edelman and Singer (2015); Rawson et al. (2013); Homburg et al. (2015); Shah et al. (2006); Verhoef, Kooge, and Walk (2016)	Stresses the importance of CXM across touchpoints, emphasizes the mindsets of customer-centric/experience orientation, and the importance of firms' capabilities.
Multichannel Research	Beneficial effects of channel integration	Neslin et al. (2006); Cao and Li (2015); Herhausen et al. (2015); Emrich et al. (2015); Emrich and Verhoef (2015)	Considers how interactions between the channels affect experience channels, the positive effects of synergies, online-offline channel integration, assortment integration.
	Specific touchpoints	Baker et al. (2002); Bart et al. (2014); Gomez et al. (2004); Mackeniz and Lutz 1989	Specific touchpoints should contribute to the customer experience at different stages.
	The interactions of multiple touchpoints to the CX	Baxendale et al. (2015); Macdonald et al. (2012); Van Nierop et al. (2011)	The impact of multiple interactions and the valence of these with multiple touchpoints on brand preference change, the frequency and positivity of interactions' contribution to brand preference change, the effective marketing tactics to induce persuasive in-store communication.
Network Perspective	Types of coordinated network and governance for such partner networks	Tax et al. (2013); Bodine (2013); Patricio et al. (2011); Patricio et al. (2008); Sampson (2012); Teixeira et al. (2012); Provan and Kenis (2007)	A network perspective that recognizes the roles of communities, experience networks, service delivery networks, and collaborator and governance mechanisms, such as customer-coordinated, service-coordinator-based,

Major Streams	Sub Streams	Authors (year)	Key Findings
			firm-coordinated networks, and participant-governed networks, plus lead-organization-governed and network administrative organizations.
Internal Firm Perspective	Firms' developing mindsets and capabilities	Homburg et al. (2015); Shah et al. (2006); Ramani and Kumar (2008); Bijmolt and Verhoef (2016)	CXM conduction affects firms; for example, firms develop an experience response, customer-centric, and interactive customer orientation, and abilities regarding customer journey design, partner-network, and data science to design CX

Several insights can be gained from **Table 2.6**, which summarizes the key findings of previous works on CXM. The first research stream focuses on the service context, specifically on the development of schemes and methods of service experience design by drawing on service-dominant logic. The second stream provides ad-hoc guidance for CXM regarding the process of strategically managing a customer's entire experience with a product or company. The third stream focuses on how interactions within the service delivery process affect customer experience, which is typically measured as customer satisfaction. Multichannel research shows that a seamless experience across different channels (through channel integration) will create a stronger CX. However, there is limited work regarding the contributions to the customer experience of multiple touchpoints across many stages. In this stream, there is a call for future studies to utilize a richer model that can examine the effects of multiple interactions of touchpoints across multiple stages; this will enable the identification of the effect of an individual touchpoint, which may change depending on when it occurs in the overall customer journey. Regarding the network perspective in the CXM domain, it is useful to adopt the service delivery network and partner network perspectives to map and analyze the customer journey. These perspectives incorporate suggestions of the need to balance the benefits and costs of delivering CX, as well as to choose appropriate governance mechanisms. Finally, the research stream of the internal firm perspective contends that to effectively deliver CX, firms require a customer-centric focus, specific capabilities, and a multidisciplinary perspective. Gaps can be readily identified in this research stream, including how to assess the performance/consequence of the firm's CXM actions and the consideration of critical moderators that will interfere with the performance of the firm's CXM.

Additionally, this thesis suggests that one can gain further insights into the concept of CXM by investigating the position of CX in its nomological network of related marketing constructs. For example, Bolton (2016) posits that interaction quality is the foundation of CX. An experience provider that performs well qualitatively when interacting with the customer evokes a strong, positive CX. Verhoef (2009) contends that an experience provider that pays individual attention to customers' needs and preferences when interacting with them evokes a strong, positive CX. Moreover, while

CX arises during the customer-experience provider's interaction, satisfaction is a subsequent evaluation that only occurs after the interaction (Oliver, 1980) and loyalty is a longer-term, more future-oriented attitude toward an experience provider, resulting in repurchase and recommendation intentions and behaviors (Dick & Basu, 1994).

The existing studies identified in **Table 2.6** have made progress in explaining how firms can manage the customer journey and experiences. However, there is scant empirical research on CX/CJ that considers how these journeys change over time. Lacking a dynamic perspective, the static research lens implies that customers' experiences are (a) temporally homogeneous, and that (b) all customers respond to firms' CX initiatives in similar ways. This is clearly not the case. An individual's perceived CXs may change throughout her consumer journey even though it involves the same providers, firm-initiated stimuli, strategies, or tactics. Moreover, the same managerial actions or marketing tactics may create different impacts on different individuals and the overall influences of the focal strategy will change over time. Thus, the dynamic perspective of CXM needs to be explored further.

Through the literature review in section 2.3, this thesis can identify knowledge gaps relating to the issues identified in sections 2.1 and 2.2. It is plain that there is very little CX/CXM research that explains how different managerial strategies exert varying effects throughout the customers' CX dynamic trajectories. There is also a lack of empirical work that builds on the findings of the conceptual work dealing with the inherent dynamism of the CX concept (Homburg et al., 2017; Kuehnl et al., 2019; Lemon & Verhoef, 2016)

Given the disconnect between Lemon and Verhoef (2016)'s conceptual paper and the empirical studies on CX, this thesis proposes and tests a dynamic perspective. Specifically, the dynamic gaps in the CX literature will be filled by (1) depicting the dynamic phenomena of consumers' experience trajectory and (2) dynamically managing consumers' experience trajectories. The term "dynamic" refers not only to the process-view of sequential CXs that constitute the CX trajectory but also to the variety of interactions among experience providers, experience receivers, external factors, and management actions that influence the evolution or change in direction of the CX trajectory.

Furthermore, Lemon and Verhoef (2016)'s conceptual work urges researchers to consider the availability of "big data" as a new approach for capturing CX data. They further suggest utilizing novel data collection techniques, such as collecting customer feedback metrics from social listening platforms and leveraging emerging techniques such as text analytics. This thesis responds to Lemon and Verhoef's call to leverage this potentially fruitful area, and thus sheds new light on the customer experience.

2.4 Propose a General Research Framework

In this section we present a basic theoretical background that helps build the general research framework for this thesis. First, we explain how to harvest CX insights from consumers' verbatim textual online reviews. Second, we offer a value co-creation perspective to develop dynamic CX management strategies; this is based on the rationale that CX is essentially co-created by experience providers (firms, brands, service providers) and receivers (customers). Third, our use of online reviews to capture CX insights leads us to the view that the managerial responses to online customer reviews may affect not only the (current) customers who create the reviews but also the subsequent (potential/new) customers who observe the response. Thus, it is crucial to include and assess the magnitude of such externality in the research framework. Fourth, to develop a "dynamic" research framework, a dynamic empirical model is needed to capture the dynamics of the CX concept. Finally, a general framework is proposed as the basis for the three empirical papers presented in Chapters 3-5.

2.4.1 Understanding CX through Customers' Textual Reviews

Text mining and other emerging techniques offer the potential to effectively measure and manage CX (Keiningham et al., 2017; Lemon & Verhoef, 2016; McColl-Kennedy & Zaki, 2019; Ordenes et al., 2014; Verhoef et al., 2016). Text can be seen as a reflection of the producer (Berger et al., 2019) in that it provides insights into the individuals that generate it (Ludwig et al., 2016; Moon & Kamakura, 2017; Pennebaker, 2011; Rude et al., 2014) and also into people's attitudes and relationships regarding other objects (Anderson & Simester, 2014; Hancock et al., 2007; Netzer et al., 2019; Ott et al., 2012). Additionally, going beyond the single individual, text can be aggregated across many creators to study larger groups or institutions (Berger et al., 2019). Given that texts reflect information about those who create them, grouping people together on the basis of shared characteristics can provide insights into the nature of such groups and the differences between them (e.g., Fiss & Hirsch, 2005; Homburg, Ehm, & Artz, 2015; Mogilner et al., 2011). Finally, texts, being shaped by their contexts, can reflect the contexts in which they are created (Boghrati & Berger, 2019; Cogn, Mehl, & Pennebaker, 2004; Garg et al., 2018). Based on Berger et al. (2019)'s suggestion, text analysis can provide insights that may not be as easily obtained by more traditional methods, such as surveys, interviews, and lab experiments. Furthermore, firms/experience providers can use this social listening tool (i.e., online reviews) to understand CX insights (Lee & Bradlow, 2011; Lemon & Verhoef, 2016; Netzer et al., 2012).

With the growing application of big data in practice, textual data, such as verbatim comments from the customer, are now generated at multiple touchpoints during the customer journey. Open-ended feedback and user-generated contents constitute excellent sources from which to mine meaning and gain insights throughout the customer journey (Tirunillai & Tellis, 2014). This thesis will leverage customers' verbatim textual reviews to offer significant CX insights and advance the approaches of CX analytics for future CX researchers and practitioners.

2.4.2 Managing CX through Value Co-Creation Perspective

Based on the rationale that customer experiences are co-created by the experience providers and the customers themselves, this thesis adopts a value co-creation perspective to develop the dynamic CX management strategies for the proposed framework.

Value co-creation has been variously defined in the literature ever since Normann and Ramirez (1994) first posited the concept of co-production. In 2000, Prahalad and Ramaswamy proposed the concept of value co-creation, whereby firms co-create a personalized experience with customers who wish to shape their own experiences. Later, Prahalad and Ramaswamy (2003; 2004) contended that the co-creation experiences become the basis for unique value; a firm cannot create anything of unique value without the engagement of individuals. Running parallel with the thinking on value co-creation, Vargo and Lusch (2004) proposed the Service-Dominant Logic, whereby customers are active participants in the relational exchange and co-production. Later, S-D logic's notion of value co-creation suggested that there is no value until an offering is used, and that experience and perception are essential to value determination (Lusch & Vargo, 2006). In 2008, Gronroos adopted the S-D logic, proposing that firms become involved with their customers' value-generating processes and expand their marketing offering to include firm-customer interactions. The same year saw Payne et al. (2008) propose that the value co-creation process involves the supplier in creating superior value propositions, with customers determining the value upon consumption of a good or service. Vargo et al. (2008) further propose that value is co-created through exchange, with resources becoming integrated into the service system, networks, and constellation. Xie et al. (2008) maintain that resource integration is a process of customer operant resources combining with firm operand resources. Ng et al. (2010) and Ostrom et al. (2010) posit that value co-creation entails a value that the customer and firm jointly create to their mutual benefit. Heinonen et al. (2010) further propose a customer-dominant logic that is adapted from S-D logic. The sites of interest in a customer-dominant logic are focusing on how a firm's service is and becomes embedded in the customers' contexts, activities, practices, and experiences, together with the implications of these for the service providers. McColl-Kennedy et al. (2012) define customers' value co-creation as the benefits realized from the integration of resources through the activities and interactions with collaborators in the customers' service networks. They envisage an all-encompassing, multiparty process that potentially includes not just the focal firm but also other market-facing/public resources, as well as customer activities and customers' personal resources.

In 2014, Ordenes et al., identified three elements of value co-creation (activities, resources, and context), which McColl-Kennedy et al. (2019) extended to five elements (resources, activities, context, interactions, and customer role).

This research framework will adopt four elements of the value co-creation perspective; that is, **A**ctivities (A), **R**esources (R), **C**ontexts (C), and **I**nteractions (I). These four elements will be proposed as an ARCI model in Chapter 4 (empirical study 2) and act as the mechanism for the purpose of CX management.

According to previous contributions on the elements of value co-creation, resources include those of both the firm and its customers; these are defined as the core competencies, fundamental knowledge, system, functions, and skills of an entity

(Macdonald et al., 2016; McColl-Kennedy et al., 2012, 2017; Ordens et al., 2014; Vargo & Lusch, 2008). Activities are defined as firms and customers performing or doing something, and they range from simple to complex (McColl-Kennedy et al., 2012; Ordenes et al., 2014). Context includes the situational context that can positively or negatively affect a customer's experience (e.g., Grönroos & Voima, 2013; Ordenes et al., 2014). Interactions are the ways in which individuals engage with others in their service network to integrate resources (McColl-Kennedy et al., 2012). As highlighted by Baxendale et al. (2015), interaction with others is important in CX. This thesis contributes to the CX management theory and practice by offering a value co-creation mechanism that integrates prior contributions in order to more effectively manage and improve CX. The proposed value co-creation mechanism comprising ARCI serves as a CX management tool. In line with the works of McColl-Kennedy et al. (2019), Macdonald et al. (2016), and McColl-Kennedy et al. (2012), this thesis adopts the perspective that customers' CX is dynamically co-created with the experience providers throughout the customers’ CX trajectories. Thus, the CX trajectories are determined, shaped, and influenced by the firms and customers’ interactions and the performance of activities through the integration of resources in specific contexts. More specific details of the literature review and theoretical development of the research framework can be found in Chapter 4 (empirical paper 2) of this thesis.

2.4.3 Managerial Response as an Alternative to CX Management

Prior literature tends to focus on the providers of online reviews, whether these be demanders, experience receivers, or customers, i.e., it explores the role played by online reviews in consumers' purchasing decisions (e.g., Chevalier & Mayzlin, 2006, Goh et al., 2013; Liu, 2006). However, from the perspective of the suppliers, experience providers, and firms, the dynamics of business owner engagement with consumers via online social media are less well understood, at least with regard to the underlying mechanisms and impacts of managerial responses to customer reviews. **Table 2.7** summarizes the research into the management responses (MRs) to customer reviews; it enumerates the results for the measurement and performance of MRs and identifies their underlying mechanisms. The table illustrates that there are inconsistencies across all of these studies not only in the components of the MRs but also in their influential consequences. For example, Ma et al. (2015) find that a service intervention by the firm may actually encourage negative redress-seeking tweets, constituting decreased review valence. Both Ma et al. (2015) and Chevalier et al. (2018) argue that negative reviews are more likely to be stimulated by MRs since potential reviewers perceive the negative reviews as being more impactful. In contrast, Proserpio and Zervas (2017) study a similar phenomenon and find increased review valence following the initiation of a managerial response. They suggest that active MR decreases the posting of negative reviews since reviewers feel concerned that their review will be more closely scrutinized.

Most of the previous literature on MR leverages lab experiments to test response strategies and the consequential variables. There are limited field studies that utilize big data and text mining techniques to examine longitudinal online reviews and online responses. Finally, based on the rationale that this thesis will leverage online consumer reviews to extract CX insights throughout CX trajectories, it is logical and necessary to explore MRs as an alternative approach to managing CX dynamics. This is an approach that is currently underexplored in the existing literature (Chen et al., 2019). More details on the literature review and theoretical development can be found in Chapter 5 (empirical paper 3) of the thesis.

Table 2.7 Summary of the Literature Review Findings regarding the Online Managerial Response

Authors	Research Context	Measures of MRs	Mechanisms of MRs	Impacts of MRs
Ma et al. (2015)	Online MR strategies for customer complaints on social networking site	Responding and not responding		An MR strategy is preferred for the customer relationship with the firm and the number of negative postings.
Proserpio and Zervas (2017)	Online MR strategies for customer complaints on rating	Responding and not responding		An MR strategy is preferred for impact on ratings and the

Authors	Research Context	Measures of MRs	Mechanisms of MRs	Impacts of MRs
	website			amount and length of subsequent negative reviews.
Wang and Chaudhry (2018)	Online MR strategies for customer complaints on rating website	Responding and not responding	Moderators: Tailored response and observability	An MR strategy is preferred for subsequent reviews and opinions.
Chang et al. (2015)	Online MR strategies for customer complaints on consumer forum	Accommodative strategy, defensive strategy	Moderator: The severity of failure (high, low, no difference)	The accommodative strategy is preferred for organizational reputation and negative WOM.
Dens et al. (2015)	Online MR strategies for customer complaints on rating website	Four types of apology, refutation, no response	Moderator: Share of negative reviews to total reviews	An apology strategy is preferred for brand attitude and positive WOM intentions.
Esmark Jones et al. (2018)	Online MR strategies for customer complaints on rating website	Responding and not responding	Moderator: Responder type (company/employee/ no difference)	An MR strategy is preferred for satisfaction, brand attitude and purchase intention.
Rose and Boldgett (2016)	Online MR strategies for customer complaints on rating website	Two types of apologies, no response	Moderator: Complaint characteristics-controllable issue	The MR and no difference between apology types is preferred for company reputation.
Schaefers and Schamari (2016)	Online MR strategies for customer complaints on social networking site	Apologies with and without solutions	Moderator: Presence of other users (brand or complaint supporting)	An apology with a solution is preferred for satisfaction with complaint handling and purchase intentions.
Van Noort and Willemsen (2012)	Online MR strategies for customer complaints on consumer and brand platforms (blogs)	Proactive, reactive, no response	Moderator: Characteristics of communication-platform of brand or platform of consumer	A proactive MR strategy is better than a reactive response for brand evaluation.
Weitzl and Hutzinger (2017)	Online MR strategies for customer complaints on social networking site	Four types of accommodative strategies, three types of defensive strategies and no response	Moderator: Credibility of response	An MR accommodative strategy is better than a defensive strategy for brand attitude, brand trust, purchase intention, and others.
Xia (2013)	Online MR strategies for customer complaints on consumer platform (forum)	Vulnerable and defensive strategy	Moderator: Sophisticated and perfect brand personality, brand relationship	A vulnerable MR strategy is preferred for satisfaction, purchase intention, positive WOM intentions.
Johnen and Schnittka (2020)	Online MR strategies for customer complaints on social	Accommodative and defensive strategy	Moderators: Contextual benefits sought by observers	No superior strategy *per se* for generating observers' perceived

Authors	Research Context	Measures of MRs	Mechanisms of MRs	Impacts of MRs
	networking site		(hedonic vs. utilitarian), level of complaint reasoning, communication style (informal vs. formal)	benefits and purchase intentions.
Chen et al. (2019)	Online MRs to online customer reviews on the two largest online travel platforms	Responding or non-responding strategy	Motivation argument: the richness of disclosure of identity information Mitigation argument: The nuance of responding targets and style	MRs have a positive impact on the volume of subsequent customer reviews. The impact of MR on review valence is not evident. Managers should provide detailed responses to negative reviews but brief ones to positive ones.
Chevalier et al. (2018)	Online MRs to customer views on travel platforms	· The initiation of MRs before and after, and · The initiation of MRs or not	· Reviewer motivations: whether reviewers are motivated by the impact of their reviews on the service providers · The effects of the presence and type of MRs on the likelihood of reviewers with different experiences posting	MRs stimulate reviewing activity, particularly negative reviews that are seen as more impactful.
Herhausen et al. (2019)	Online MR strategies to customer complaints in online brand communities	· Intensity of empathy · Intensity of explanation · Variation in MRs: variance in the proportion of empathic and explanatory of words across all firm responses MR control variables: ·Compensation ·Apology ·Channel change	· High and low arousal emotions · Structural tie strength in brand communities · Linguistic style match between reviewers and brand community	· The MR strategy must be tailored to the intensity of arousal to limit the virility of potential online firestorms. · The impact of initiated firestorms can be mitigated by distinct MRs over time. · The effectiveness of different disengagement MRs varies with their timing.
Kumar et al. (2018)	Online MRs to customer reviews on digital platforms	Responding or not	· Online review rating received by the focal firms	· Online MRs increase focal business performance.

Authors	Research Context	Measures of MRs	Mechanisms of MRs	Impacts of MRs
			· Competition intensity from the focal firm's perspective	· When firms are/are not in direct competition, online MRs lower/benefit nearby businesses' performance.

Including MRs as a CX managerial tool in the proposed research framework is theoretically essential to providing a complete picture; this is partly so that a dynamic CX management theory may be developed but it is also crucial to enabling experience providers to develop appropriate strategies for responding to consumers' online reviews. This is because unless the dynamic effects and underlying mechanisms of online MRs can be quantified, it is unclear to practitioners whether, when, and how they should actively embrace and respond to consumer comments.

2.4.4 The Need for a Dynamic Perspective to Investigate CX Dynamics

Given the recent attention in marketing to the description of the customer journey, dynamic models have become highly relevant. Using these dynamic models, one can capture the transitions of customers from state to state. The definition of state varies and depends on the research context. For example, states may refer to the relationship quality that customers have with a brand/experience provider, ranging from a very weak to a very strong one. The customers or firm traverses a set of latent states over time, within each of which the customer or firm probabilistically behaves in a particular pattern. These states are latent, and the Hidden Markov Model (HMM), as one of the dynamic-modeling methodologies, has been used to model how a sequence of observations is governed by the transitions in a set of latent states.

Netzer et al. (2008) suggest using HMMs to capture customer relationships empirically, theorizing that the latent relationship can be characterized by discrete relationship states. Kumar et al. (2011) capture the effect of marketing conduct on business buying behavior through an HMM. Montoya et al. (2010) attempt to allocate marketing resources dynamically on the basis of a customer's hidden relationships and use firms' beliefs about their customers' relationship state as a state variable. Schweidel et al. (2011) use an HMM to investigate the relationship between a customer’s hidden state and a customer’s lifetime value. Li et al. (2011) apply an HMM to understand how to cross-sell the right product to the right customer at the right time. Some researchers suggest the importance of acknowledging the customer relationship/psychological/latent states as a means of conducting CRM more effectively, such that certain marketing actions might be more effective in certain states than in others (Luo & Kumar, 2013; Zhang et al., 2016).

In a word, the main objective is to be able to leverage a dynamic model to capture the dynamics within customer experience trajectories over time. This thesis plans to employ HMM to capture the dynamics in CX from observable data (i.e., the collected online textual reviews) and understand how CX management strategies may influence the CX dynamics. The latent states in the proposed framework represent customers' CX performance states (study 1) or firms' CX performance states (study 2). We argue that CXs are dynamic in nature so, as customers move across their CX performance states, certain CX management strategies might become more effective than others or even amount to little more than a waste of resources.

2.4.5 The Proposed General Research Framework

Based on the theoretical background outlined in sections 2.4.1-2.4.4, a general research framework is proposed that expresses the core essentials of the thesis and links the three empirical papers. The research framework, presented in **Figure 2-1**, can be used to answer a crucial question that runs throughout this PhD thesis: given a customer's current CX state, or a firm's CX performance state, what is the most effective CX management strategy for migrating to a higher-performing state or at least preventing it from moving to a lower one?

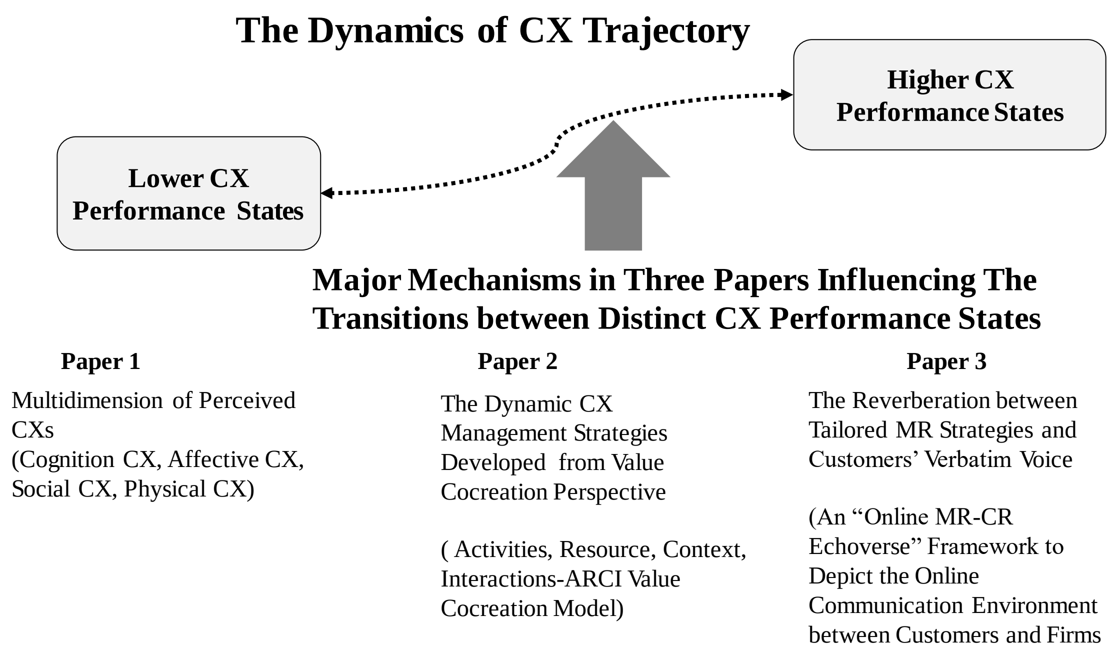


Figure 2.1 The General Research Framework

Chapter 3 : Study 1

Customer Experience Trajectories: Building a Dynamic Model from Repeat Customers' Verbatim Reviews

Abstract

Although a better understanding of what drives repeat customers is highly relevant for marketing practice, few studies provide conceptual and empirical insights into the experiences of repeat customers and how those experiences might be managed. Furthermore, most approaches that analyze relevant customer experience issues are static. We propose a customer experience trajectory (CET) framework that takes a dynamic perspective. We propose that the building blocks of the CET framework are repeat customers' CX performance states, comprised of their behavioral performances, from lower to higher levels. Two mechanisms are offered to explain the influences on repeat customers' migrations between CX performance states: four dimensions of customer experience and six managerial-related variables. Our aim is to understand the evolution of the experience trajectories of segmented groups of repeat customers and examine how customers in different segments respond differently to the migration

mechanisms. We argue that repeat customers migrate throughout their CX performance states over time and that not all migration strategies are equally valid. Building on a unique dataset of 3,166 repeat customers who made 31,736 comments on Airbnb, we apply a hidden Markov model (HMM), and leverage text mining and natural language processing techniques to transform the verbatim textual data into structured numeric metrics for the HMM. We identify three CX performance states and two repeat customer segments. We parsimoniously capture the dynamic effectiveness of the migration mechanisms, moving beyond the extant customer experience literature to a more fine-grained understanding of customer experience and generating fresh management insights into the dynamics of the customer experience.

3.1 Introduction

Significant empirical evidence reveals that the ACSI (American Customer Satisfaction Index), a portfolio of stocks selected according to customer satisfaction levels, produced 518% rate of return from 2000 to 2014; this is a satisfying result by any standards but especially when compared with the 31% increase experienced by the S&P 500 (Fornell, Morgeson, & Hult, 2016). The obvious inference is that creating a satisfying customer experience is crucial for companies who wish to not only better manage their customer relationships but also generate significant financial benefits. In practice, firms have invested heavily in their ability to plan the entire customer experience, employing managers who are responsible for “customer experience management”, i.e., for making the customer experience remarkable. However, these customer experience practitioners may be overlooking an underlying question: will the experience of first-time customers differ from that of repeat customers? One might instinctively jump to the conclusion that “repeat customers” must be in a statically satisfied state, given their observable repeating patronage behaviors. Hence the deductive hypothesis that repeat customers are satisfied and therefore loyal. For marketing practitioners, the consequence of such thinking means that a piece is missing from the overall picture of customer experience management regarding repeat customer retention.

In academia, several significant contributors primarily focus on measuring customer experience (Brakus, Schmitt, & Zarantonello, 2009; Grewal, Levy, & Kumar, 2009; Puccinelli et al., 2009; Verhoef et al., 2009). Researchers agree that the total customer experience is a multidimensional construct involving cognitive, emotional, behavioral, and social components (Lemon & Verhoef, 2016; Schmitt, 1999; 2010; Verhoef et al., 2009). Equally importantly, the framing of the consumption process as a journey is consequential, with recent research underscoring the importance of examining the customer journey to understand the customer experience. The customer journey is defined as the process through which a customer goes with an organization across all stages and touchpoints, comprising the customer experience (Lemon & Verhoef, 2016). It is widely believed that creating positive experiences within the customer journey at multiple touchpoints will result in improved performance, such as improved customer loyalty and word of mouth (WOM) (Court et al. 2009; Edelman, 2010; Homburg, Jozic, & Kuehnl, 2017). However, given the relatively nascent state of the customer experience literature, there is limited empirical work directly related to customer experience and the customer journey (Lemon & Verhoef, 2016). Specifically, the majority of customer experience studies focus on the positive relationship between consumer experience and desired customer performance from a snapshot perspective (e.g., Brakus et al., 2009; Gentile et al., 2007; Grewal et al., 2009; Holbrook & Hirschman, 1982; Lemke et al., 2011; Schouten et al., 2007; Vargo & Lusch, 2008) while ignoring the dynamic interactions among customer experience, customer behaviors, and managerial actions. These would ideally be considered from a trajectory perspective that evolves over time. We thus address the first research gap in the customer experience/customer experience management literature.

Although much of the research on customer dynamics has investigated customer retention and churning dynamics (Fader & Hardie, 2010), few customer dynamic studies have empirically examined the dynamics of repeat customers' experience. Only a relatively small body of work on customer dynamics has considered the possibility that customer relationships might deteriorate yet continue (Jap & Anderson, 2007; Reinartz & Kumar, 2000; 2003). Consideration of this kind of dynamic possibility is essential when we are looking at the relationships between firms and their repeat customers because the repetition of consumption occasions is not automatically related to customer profitability (Du, Kamakura, & Mela, 2007). We therefore identify the dynamic interactions between repeat customers' experiences and their preferential behaviors as the second knowledge gap in the customer dynamic literature. Thus, for both practitioners and scholars in the customer experience realm, it is essential to gain a better understanding of repeat customers' experience dynamics in the business-to-customer (B2C) setting.

To close these knowledge gaps in the customer experience (CX) and customer dynamic domains, we propose building a dynamic model to depict the co-evolution phenomenon between experience dynamics and behavior dynamics. We call this research framework, derived from the dynamic perspective, the customer experience trajectory (CET). We define CET as existing customers having repeated encounters with the same experience providers, where existing customers' previous experiences influence their current and future experiences. The building blocks of the CET framework are repeat customers' behavioral performance from lower to higher levels of CX performance states, as evidenced by expressions of their revisit intentions, referral intentions, compliments, and complaints. The evolution of repeat customers' CETs is expressed by their migrations among different levels of CX performance states. We further investigate the dynamic impacts of two mechanisms on the migrations of CX performance states: (1) the multidimensions of consumer experience; and (2) real-world, manager-related actions in the field settings. Our goal is to identify how different mechanisms vary in terms of their effectiveness for migrating repeat customers throughout their CETs and enhancing their preferred behavioral performances.

Through establishing the CET research framework, we aim to answer the following three major research questions: (1) How do repeat customers' CETs evolve over time? How many CX performance states can be identified ? Can repeat customers be segmented into different groups? (2) How do the migration mechanisms influence the transition across different CX performance states over time? How can we decompose the short- and long-term effectiveness of the migration mechanisms? (3) Can different segments of repeat customers respond differently to migration mechanisms as they move across their CX performance states? How might an experience provider best use our findings to improve repeat customers' experiences and trigger the desired customer behavioral performance?

The contributions of this paper are threefold. First, we empirically disentangle the dynamic nature of repeat customers' experiences through testing the proposed CET framework. Second, we offer managerial insights into repeat customers' experience management by identifying four major dimensions that act as migration mechanisms, reflecting the unique transition patterns between CX performance states throughout repeat customers' CETs. We also examine six management-related activities that influence migration across the CX performance states. Third, by leveraging the empirical results of this study, experience providers can design experiences that target distinct segments of repeat customers in different CX performance states, emphasizing the importance of tailoring the marketing resources to a specific segment during a particular CET stage. We contend that, to be effective, the strategy for managing the experience of existing, repeat customers must identify the right targets at the right time, highlighting what matters to repeat customers and which actions are required.

3.2 Literature Review and Theoretical Framework Development

In this section, we aim to provide a solid theoretical background for our CET research framework. To do so, we first examine the existing CX literature to bring together what we know about customer experience and its multidimensionality. Second, we link customer experience to its dynamic nature. We propose the customer experience trajectory (CET) as a construct and examine its existing definitions, before turning to the research streams on customer dynamics and HMM. The goal is to leverage the approaches of these research streams to capture the dynamic nature of CET. Then, by integrating field-based insights that pertain to our research context, we introduce the migration mechanisms that managers can use to influence repeat customers' migration throughout the CETs. Finally, we present the research framework; namely, the repeat customers' CET model.

3.2.1 Multiple Dimensions of the Customer Experience (CX)

CX is a central focus of marketing theory and practice (McColl-Kennedy, 2019). Schmitt, Barkus, and Zarantonello (2015) suggested that every service exchange leads to CX, regardless of its nature and form. Meyer and Schwager (2007) broadly defined CX as a customer's internal and subjective response to any direct or indirect contact with a company. Gahler, Klein, and Paul (2019) characterized CX from the customer perspective as subjective and holistic, tracing holism to Gestalt psychology and building on the principle of totality (Koehler, 1938; Koffka, 1935; Wertheimer, 1945). According to this school of thought, every component of the human mind is interlinked. Thus, individuals perceive experiences holistically by considering all of the internal and behavioral aspects simultaneously. Although multiple definitions of CX exist in the literature, we will focus our attention on the major accepted definitions that regard it as multidimensional and holistic in nature. For example, Schmitt (1999) adopted a multidimensional view and identified five types of experience: sensory (sense), affective (feel), cognitive (think), physical (act), and social-identity (relate). Gentile, Spiller, and Noci (2007) contended that the consumer experience can be defined as a set of interactions between a customer and a provider, which provokes a reaction from the former and implies his or her involvement at different levels (rational, emotional, sensorial, physical, and spiritual). Verhoef et al. (2009) defined CX as holistic in nature, involving the customer's cognitive, affective, emotional, social, and physical responses to the retailer. Brakus, Schmitt, and Zarantonello (2009) defined brand experience as consisting of four separate, albeit related, dimensions: sensory, affective, intellectual, and behavioral. De Keyser et al. (2015) described the consumer experience as comprising cognitive, emotional, physical, sensorial, spiritual, and social elements that mark the customer's direct and indirect interaction with the other market actors. Schmitt, Brakus, and Zarantonello (2015) considered CX to be holistic in nature, incorporating the customer's cognitive, emotional, sensory, social, and spiritual responses to all interactions with a firm. Other research argues that the physical factors of CX include multisensory, ambiance, physical features, and artifacts (Walls et al., 2011). Some researchers have studied the cognition factors in terms of the disconfirmation paradigm, which predicts satisfaction as a function of a comparison between expectations and performance (e.g., Bearden & Teel, 1983; Labarbera & Mazursky, 1983; Oliver, 1980; Oliver & Desarbo, 1988). Following the abovementioned discussion of the literature on CX, we argue that all of these factors may be classified under four major dimensions. In summary, we observe that the consumer experience construct is holistic and multidimensional in nature and involves the customer's cognitive-rational, affective-emotional, social-relational, and physical-sensory responses to the product/service providers, in line with the four primary systems commonly studied in the fields of psychology and sociology (Anderson, 1986; Pinker, 1997). We will now discuss this further.

First, the cognitive-rational dimension involves thinking, conscious mental processing, and problem-solving (Gentile, Spiller, & Noci, 2007) and captures the functional aspect and value of experiences to the customer (Verhoef et al., 2009). Customers, during their interactions with an experience provider, use their abilities of imagination, understanding, and reasoning to engage in the cognitive process, which covers their thoughts, ideas, insights, and learning (Gentile et al., 2007; Hirschman, 1984). The fact-based dimension is generally impersonal, outcome-oriented, and objective in nature (Schlosser, White, & Lloyd, 2006). In addition, the affective-emotional dimension involves the customer's affective system through the generation of emotions, feelings, moods, and sentiments (Gentile et al., 2007). Customer interaction with experience providers can also evoke affective responses and might be enjoyed for their own sake, regardless of functional considerations. The pleasure that the experience offers, regardless of its ability to facilitate a specific consumption task, is thus a vital dimension of CX (Babin, Darden, & Griffin, 1994). This dimension reflects an appreciation of the fun of the experience and reflects more than a simple achievement-oriented purchase opportunity (Childers et al., 2001; Mathwick, Malhotra, & Rigdon, 2001). Third, the social-relational dimension refers to the warmth, sociability, and feelings of human contact that the experience confers (Gefen & Straub, 2003). Customer interaction forms a social context in which the customers and experience providers can interrelate, resulting in a sense of social belonging and relationship building (Gentile et al., 2007). The extant research shows that this dimension of experience can increase the perceived tangibility and feeling of psychological closeness to a product (Darke et al., 2016). Finally, the physical-sensory dimension of CX includes aspects that stimulate sight, sound, smell, taste, or touch (Gentile et al., 2007). Moreover, during interactions with the experience providers, customers exhibit behavioral responses through their bodily movements and physical actions (Schmitt, 1999), such as when they test-drive a new car prior to purchasing it. Sensory appeals refer to the representational richness of mediated environments that stimulate the customer's senses (Steuer, 1992), such as the perception of beauty; thus, aesthetically pleasing stimuli form part of this sensory appeal.

In summary, we suggest that CX is a multidimensional construct, focused on a customer's subjective and holistic responses to a firm's offerings, created not only by those elements that the firm can control (e.g., service interface, price, retail atmosphere) but also by elements that lie beyond the firm's control (e.g., consumers' shopping purpose, motivation, and inner value). We contend that customers' subjective and holistic responses to their experiences can be categorized under four major dimensions: (1) physical-sensory, (2) cognitive-rational, (3) affective-emotional, and (4) social-relational, which is in line with the four basic systems—cognition, affect, relationships, and sensations—commonly studied in the fields of psychology and sociology (Anderson, 1986; Pinker, 1997). We next introduce the dynamic nature of the customer experience by reviewing the related literature and develop the focal concept of this current research: the customer experience trajectory.

3.2.2 Customer Experience Trajectory (CET)

Several researchers' perspectives can be leveraged to understand our focal concept: CET. The process perspective of marketing suggests that firms are broadening their thinking by considering how to design and manage the entire process that is experienced by a customer. For example, Howard and Sheth (1969) proposed a model to illustrate the customers' buying process, from need recognition to purchase to evaluation. Lavidge and Steiner (1961) created their process model by adapting the attention-interest-desire-action (AIDA) model. Subsequent researchers modeled the buying process of business customers (Webster & Wind, 1972), Neslin et al. (2006) built a process from problem recognition to search to purchase to after-sales, using multiple channels. Schmitt (2003) further developed this process approach and noted the importance of tracking touchpoints throughout the customer decision-making process. Similar theoretical perspectives include the path-to-purchase, purchase, or marketing funnel (e.g., Court et al., 2009; De Haan, Wiesel, & Pauwels, 2016; Li & Kannan, 2014). These models provide the foundation for the customer decision journey or customer purchase journey

(Lemon & Verhoef, 2016), referring to the process that a customer follows across all stages and touchpoints, thereby producing CX.

Bolton and Lemon (1999) showed that prior experience influences current satisfaction, which in turn influences future usage. Moreover, Fournier's (1998) research suggested that the dynamic effects of CX can occur within customers, as the customers themselves change over time following repeated experiences with a product/service or after a specific experience. Sheth and Parvatiyar (1995) suggested that customer decisions become routinized, and that extraordinary experiences have long-lasting effects (Arnould & Price, 1993). Neslin et al. (2006) recognized that CX is not limited to the customer's interaction in the store alone but is rather impacted by a combination of experiences that evolve over time, including the search, purchase, consumption, and after-sales phases of the experiences. Verhoef, Neslin, and Vroomen (2007) highlighted the "interrelationships" between channel attitudes in different purchase phases. Verhoef et al. (2009) argued that consumer experiences may develop in multiple channels and through repeated experiences within a given channel. Lervik-Olsen, Van Oest, and Verhoef (2015) stated that past experience can affect current experience through expectation formation and stickiness in experience evaluations.

Lemon and Verhoef (2016) conceptualized CX as a customer's journey entailing a dynamic and iterative process. Their process model encompasses (1) previous experience (t-n) composed of the pre-purchase stage, purchase stage, and post-purchase stage, (2) current CX (t), which also includes the pre-during-post-purchase stages , and (3) future experience (t+n) and the three stages of pre-during-post-purchase. Lemon and Verhoef (2016) noted that it is crucial to consider how past experience, at each stage of customers' experience (pre-purchase, purchase, and post-purchase), may influence their current experience, as does the feedback effect between their current and past experiences, and these unite (e.g., exert a carryover effect) to influence future experiences. Lemon and Verhoef (2016) ultimately conceptualized CX as a customer's journey with a firm over time during the purchase cycle across multiple touchpoints. They conceptualized the total CX as an iterative and dynamic process, flowing from pre-purchase to purchase to post-purchase, incorporating past experience as well as external factors. McColl-Kennedy et al. (2019) viewed CX as a process composed of interactions and activities across multiple touchpoints. They noted that touchpoints can also occur across several repetitions of service, especially where customers repeatedly deal with the same service provider.

Despite these discussions, one might still ask: "is there any difference between CET and the customer journey?" Scholars may consider that CET is included in the customer journey; after all, both have the common goal of producing superior customer experiences. We agree with this argument since the customer journey is relatively broad, with three types of "multi-focus" in one concept: multi-experiences (previous/current/future experiences), multi-purchase stages (pre-purchase, purchase, post-purchase), and multi-touchpoints (brand owned, partner owned, customer owned, social external). To address our research question effectively and focus on repeat customers' experience dynamics, we demarcate CET from customer experience by shedding light on one of the multi-foci, namely multi-experiences. Thus, in line with McColl-Kennedy's perspective, we propose a concept, the CET, which we define as focusing on "current/existing" consumers' repeat experiences in the same consumption context (e.g., customers' multiple experiences of hotel stays over time), where the previous experiences influence subsequent experiences, involving customers' subjective responses both multidimensionally and holistically.

3.2.3 The Customer Dynamics Literature on Understanding CET

Some researchers suggest that the dynamic effects of CX can occur within customers because the customers themselves change over time following repeated experiences with a product (Lemon & Verhoef, 2016). Previous researchers also agree that a memorable CX serves to improve consumers' emotional, cognitive, and behavioral values and creates closer bonds with the provider, consequently promoting a high level of satisfaction (Lo, 2012), positive WOM (Kim et al., 2010) and an enhanced revisit intention (Hung et al., 2016). Other studies recognize that the affectional factors experienced during the consumption trajectory can also have a significant influence on loyalty judgments (e.g., Mano & Oliver, 1993; Westbrook, 1987; Westbrook & Oliver, 1991).

To develop a theoretical foundation for the CET, we borrow concepts from the customer dynamic (CD) realm; CD scholars agree that relationships evolve over time and are fundamentally dynamic in nature (Harmeling et al., 2015; Kozlenkova et al., 2017; Palmatier et al., 2013; Zhang et al., 2016). Many empirical studies on relationship management use the term "stage" to identify empirical differences and capture developments involving the growth, maturation, and decay of relationships over time (Heide, 1994; Hibbard et al., 2001; Jap & Anderson 2007; Jap & Ganesan, 2000). As Grayson and Ambler (1999) note, the length of the relationship changes the nature of the relational constructs, and the exact nature of these relational dynamics remains elusive.

Moreover, several crucial notions have been proposed by satisfaction researchers, who devote attention to the dynamic development of customer satisfaction (e.g., Bolton & Drew, 1991; Boulding et al., 1993; Mittal et al., 1999) in light of the concept that current customer satisfaction affects future expectations.

Other researchers have investigated CD as they relate to the theoretical perspectives of choice modeling (Montoya, Netzer, & Jedidi, 2010; Netzer, Lattin, & Srinivasan, 2008), behavioral changes over time (Rust & Verhoef, 2005), retention rates (Fader & Hardie, 2010), and customer portfolio management (Homburg, Steiner, & Totzek, 2009). Specifically, customer portfolio management moves existing relationship marketing models into the realm of CD by incorporating conversion and switching probabilities. In Johnson and Selnes (2004)'s study, conversion probabilities refer to the progression of customers from one type of relationship to another, whereas switching probabilities refer to customers deserting the firm for a competitor's product. Johnson and Selnes (2004)'s findings suggest that even marginal increases in a firm's conversion probabilities and the corresponding reduction in switching probabilities will result in a significant increase in the value of a firm's customer portfolio. Previous contributors also agree that consumers' loyalty behavior and attitudes evolve over time (e.g., Dick & Basu 1994; Johnson, Herrmann, & Huber, 2006; Jones & Sasser, 1995; Ngobo, 2017; Oliver, 1999).

Given the relatively nascent state of the CET literature, there is limited empirical work directly related to CX dynamics or the CET (Lemon & Verhoef, 2016). Thus, we argue that it is necessary to leverage a dynamic perspective to depict the evolution of repeat customers' CETs. An effective approach employed by previous scholars to capture dynamics in datasets is the Hidden Markov Model (HMM) (e.g., Luo & Kumar, 2013; Montoya, Netzer, & Jedidi, 2010; Zhang, Netzer, & Ansari, 2014). Using HMM, one can capture the transitions of customers from one state to another. The definition of state varies and depends on the research context. In this paper, states refer to the repeat customers' behavioral performances, ranging from a lower to higher level, which we call CX performance states. Repeat customers transition among a set of CX performance states over time, within each of which they probabilistically behave in a particular way and are influenced by the migration mechanisms discussed in the next section, which is concerned with the conceptualization of our proposed CET model (section 3.2.4).

3.2.4 The Conceptualization of Customer Experience Trajectory (CET)

The primary goal of this study is to empirically understand the dynamic, evolutionary, and changing nature of the CET. To this end, we propose that the evolution of CET can be disentangled by examining the co-evolution phenomenon between the desired customer behaviors/intentions and their responses to the different dimensions of experience throughout the trajectory. We argue that both customer behavior (CB) and customers' responses to their experiences change over time. Despite previous contributors' clear recognition that the customer trajectory should be viewed from a dynamic perspective, the co-evolution of customers' desired behaviors and experience dynamics has not been studied in this manner. We further argue that the multifaceted, dynamic nature of consumer experience could explain and explicitly capture the changes, migrations, or varieties of CB dynamics within the trajectory over time. To the best of our knowledge, this is the first study to examine the co-evolutionary phenomenon in the CX literature. We propose the concept of "co-evolution" to describe the phenomenon of joint dynamism existing in both CX and CB throughout the CET.

Figure 3.1 (a) presents the conceptualization of CET from the dynamic perspective, depicting the CX performance states and how customers can transition between states across time points. From a dynamic perspective, we assume that the CX performance states are hidden and will change over time, being unknown *a priori* and so having to be identified from the data. We characterize each CX performance state by the level of customers' expressed revisit intention, recommendation, compliments and complaints (in ascending order). Therefore, a hidden state in this study can represent the strength of the experience quality between a customer and an experience provider. That is, the higher the perceived experience quality, the higher the CX performance scores represented by customers' referral, revisit, and compliment expressions. In addition, by knowing the latent CX performance state for the previous time period and the transition probabilities, experience providers can estimate the probabilities of each repeat customer being in each state during the current period. We propose that repeat customers are likely to shift CX performance states over time and we further assume that the multidimensions of CX as well as management-related actions can cause a shift in their states (discussed in the next paragraph). A knowledge of such information facilitates the strategic implementation of optimal resource allocation.

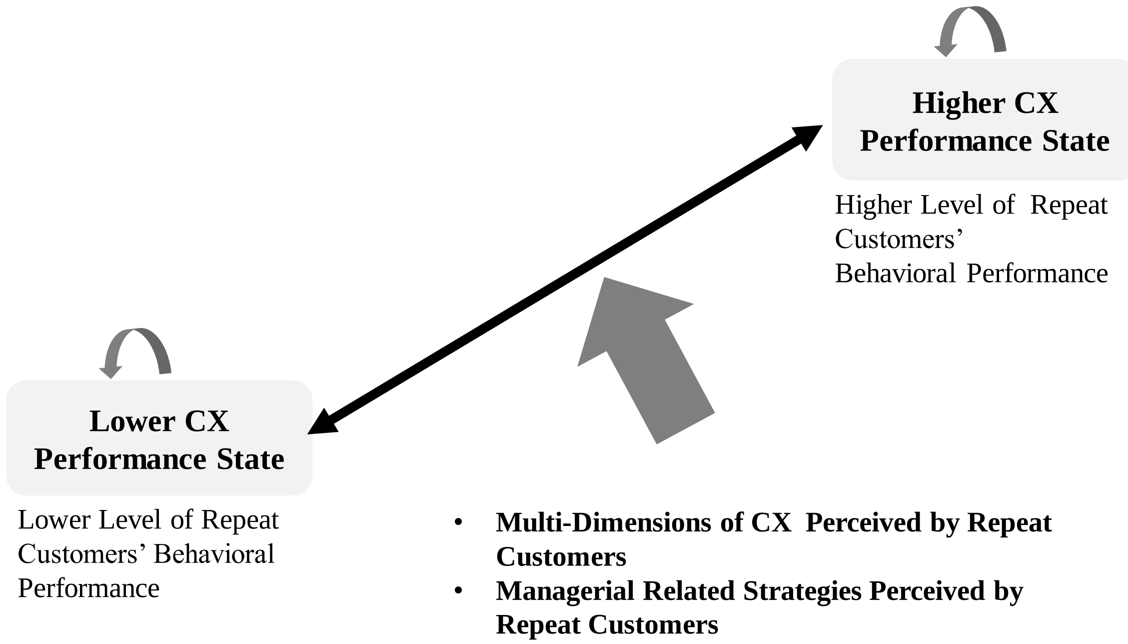


Figure 3. 1 (a): The Framework for Conceptualizing CET

Migration Mechanisms of the CET

Gahler et al. (2019) argue that customers with a strong and positive CX are more satisfied, more inclined to continue their relationships with the experience provider, and tend to express favorable attitudes, including repurchase and recommendation intentions. Biedenbach and Marell (2010) conclude that there are causal relationships between positive CX and preferred brand attitudes. Schmitt (2003) suggests that there are positive associations among satisfying experience, customer acquisition, customer retention, and add-on selling. Drawing on reasoning by Gahler et al. (2019) and other contributors, we infer that the CX performance states are expressed by repeat customers' behavioral/attitudinal outcomes, such as referrals and re-patronages, as well as their expressions of compliment and complaint.

We then extend the concepts of CRM and CX management to develop the migration mechanisms that will influence repeat customers' transitions among their CX performance states. For example, the research into relationship management models identifies relational state migration through antecedents of relationship development that are under managerial control (e.g., Palmatier et al., 2006; Zhang et al., 2016). Tax, McCutcheon and Wilkinson (2013) describe three types of service delivery network, one of which is the firm-coordinated framework in which the firm takes the lead role in connecting and coordinating all aspects of the customer's experience. In the firm-coordinated network, the firm obtains greater control, suffers less uncertainty, and gains additional insights into the entire customer experience (see also Patrício et al., 2011; Sampson, 2012). Managing the CX also affects the firm's performance. In a CRM context, Ramani and Kumar (2008) demonstrate that relationship management exerts a positive impact on business performance.

Much of the existing CX research highlights the role of CX as a critical determinant of marketing outcomes, such as customer satisfaction and loyalty (e.g., Brakus et al., 2009; Klaus & Maklan, 2012; Lemon & Verhoef, 2016). Based on this rationale, we model the multiple dimensions of CX as migration mechanisms to determine the transition/migration of each CX performance state. A migration mechanism is the unique pattern of changes in CX performance states that leads to migration. In line with Gahler et al. (2019)'s argument, we propose the four dimensions of CX (physical-sensory, cognitive-rational, affective-emotional, and social-relational variables) as the migration mechanisms, reflecting the unique pattern of changes to the state variables, comprised by repeat customers' behavioral and attitude outcomes.

In addition to considering these four migration mechanism dimensions of CX, we also consider management-related variables over which the experience providers have direct control. Integrating field-based insights from our research settings, we argue that the seller has direct control over, *inter alia*, the six Airbnb website evaluation criteria for the staying experience, namely (1) accuracy, (2) cleanliness, (3) check-in, (4) location, (5) communication, and (6) value. These variables should affect customers' perceptions of their experience and influence their migration across the CX performance states. Therefore, we investigate two migration mechanisms in the HMM model – (i) the four dimensions of CX and (ii) the six management-related variables. The combination of a supplementary literature with field-based observation allows us to provide a theoretically and empirically solid conceptualization of the two migration mechanisms. **Figure 3.1 (b)** presents the CET research framework in a more comprehensive way.

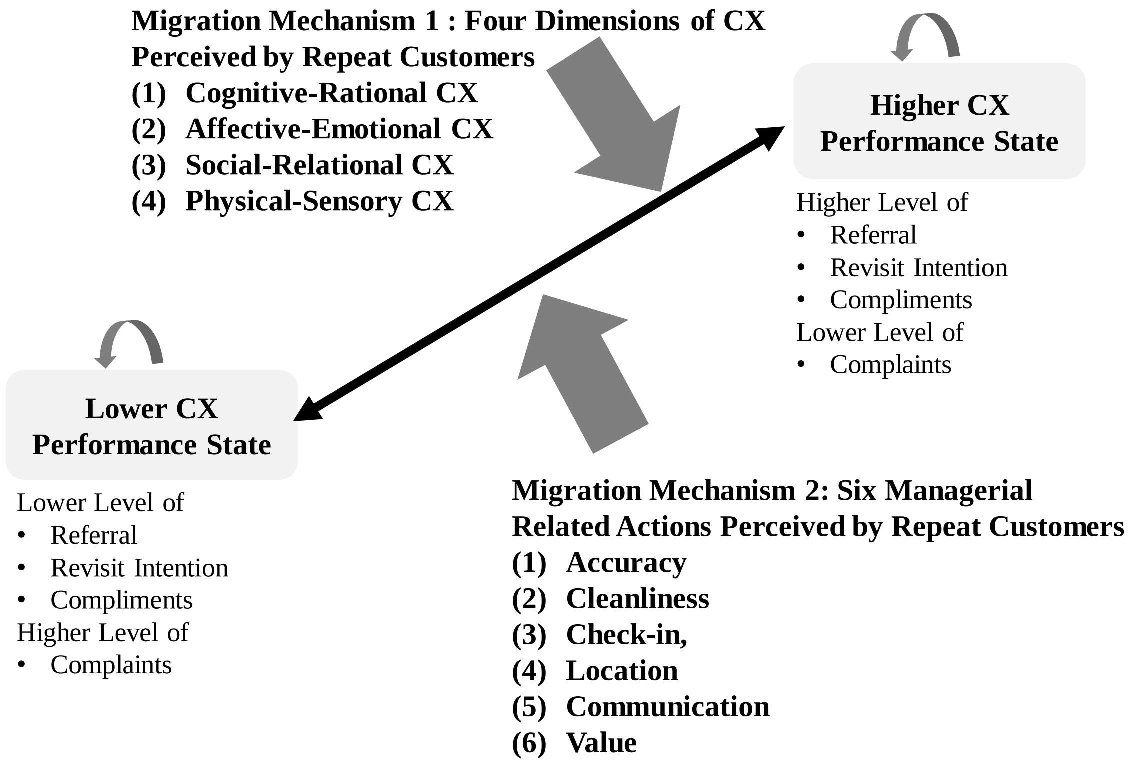


Figure 3.1(b) A Comprehensive Perspective of the CET Research Framework

3.3 Methodology and Data

3.3.1 The Choice of Methodology

The Hidden Markov Model (HMM) is well suited for inferring latent states from observed behaviors, such that customers can flexibly migrate between different states (Luo & Kumar, 2013; Montoya, Netzer, & Jedidi, 2010; Zhang, Netzer, & Ansari, 2014). Moreover, the HMM enables researchers to model the time-varying effects of marketing strategies/management actions via the formulation of latent (hidden) states. For example, Zhang, Waltson, Palmatier, and Dant (2016) apply a multivariate HMM to identify the buyer-seller relationship states, capturing customers' migrations across relationship states through three positive and two negative migration mechanisms. Ngobo (2017) uses HMM to uncover three latent states to depict the trajectory of customer loyalty and the effectiveness of certain marketing actions, such as the private label policy, feature advertising, product display, and store pricing policy in influencing customers' transition across loyalty states. Chen, Wei, and Zju (2017) characterize the dynamics of user contributions in online communities using an HMM with latent motivational states. They focus on three mechanisms (reciprocity, peer recognition, and self-image) through which users transition between the latent states.

The metrics of employing HMM to study our CET research framework are flexibility and parsimony. Beyond the flexibility of being able to empirically identify the number of latent states, HMM can show the degree of transience or stickiness of the different states. These properties are well suited to the present study's focus on repeat customers' experience trajectories. Moreover, recent work has increased the value of the HMM in resolving marketing research issues by incorporating unobserved heterogeneity across individuals (e.g., Kappe, Blank, & DeSarbo, 2018; Montoya et al., 2010; Schweidel & Knox, 2013), which may be presented in both state-dependent and transition parameters. Unobserved heterogeneity exists in many marketing applications, and failing to account for these leads to biased parameters and inaccurate managerial insights (see Netzer, Ebbes, & Bijmolt, 2017, for a discussion of the consequences of ignoring unobserved heterogeneity in the HMM). However, as the true nature of the unobserved heterogeneity is usually unknown *a priori*, the selection of a discrete or continuous distribution tends to be an empirical issue (Andrews, Ansari, & Currim, 2002; Michalek et al., 2011). Typically, a discrete distribution leads to a latent class model, while a continuous distribution leads to a random coefficients model (Wedel et al., 1999). Netzer et al. (2017) encourage researchers to account carefully for unobserved heterogeneity if heterogeneity is to be disentangled from dynamics. Thus, this present study will incorporate patterns of unobserved heterogeneity into the HMM to address both practical and methodological concerns. We use HMM to capture the transitions of repeat customers, testing the proposition that repeat customers transition among a set of CX performance states, within each of which they probabilistically behave in a particular pattern and are influenced dynamically by distinct migration mechanisms.

3.3.2 The Choice of Data Type

With the popularity of online media, consumers have ceased to be passive recipients of the information provided by firms or brands; consumers now actively and regularly share their experience with others on online platforms such as Airbnb, yelp, TripAdvisor, or Amazon. The body and popularity of textual information generated by customers in the new online media is relatively massive and growing rapidly (Tirunillai & Tellis, 2012). This richness is attractive to marketing researchers since it opens a large-scale window into the world of "why" in the field, and it does so in a scalable manner (Berger et al., 2020). According to Berger et al. (2020), text provides real-time consumer-related information that can shed light on the consumer experience; as such it offers an alternative to traditional marketing research tools. Furthermore, CXM researchers and practitioners may adhere to the logic that firms can reap business advantage from CXM through a better understanding of what affects CX. However, a primary challenge for marketing practitioners and researchers concerns how to obtain reliable and generalizable survey or field data about factors that are housed in the mental models, lifestyles, value systems, and beliefs of focal customers. Consumers' self-generated content offer a solution to the above-mentioned challenge and this naturally occurring data can be used to assess CX related constructs in the field. We argue that lab and survey data are pre-defined concepts designed by researchers and oriented by their research designs; they can be seen as research-centered data sources. In contrast, consumers' self-generated text data reflects information about the consumers that created it and the contexts in which it was created. The text that people produce provides insight into the individuals themselves, shedding light on who they are in general, whether this is in terms of their stable traits or the customer segments of which they form a part (Moon & Kamakura, 2017), and how they may be feeling or what they may be thinking at the moment of text production (i.e., their states). This information is relatively consumer-centered compared to pre-defined survey or lab data.

Following this reasoning, we have chosen to use a form of text data in this current study; namely, customers' verbatim reviews. The goal in employing unstructured data (UD) is to generate new insights that can supplement and complement the traditional data sources, such as surveys, archival sources, or transaction data. The UD can be of practical assistance in identifying the salient issues (Gopalkrishnan, Steier, Lewis, & Guszcza, 2012). As presented in **Table 3.1**, the self-generated UD reflects the unique characteristics of the text producer, in our case the repeat customer, and provides insights into the person's attitudes or relationships regarding the service providers – whether the person liked or hated a hotel stay.

Balducci and Marinova (2018) define UD as a single data unit in which the information offers a relatively concurrent representation of its multifaceted nature without predefined numeric values. The first characteristic of UD (a lack of numeric values) means that UD lacks predefined numeric assignments for the constructs of interest, so researchers must conduct manual or automatic coding prior to the analysis. A single unit of UD possesses multiple facets, each of which offers unique information. This enables the researcher to select and analyze facets according to the researcher's specific research goals. The second characteristic of UD is concurrent representation. The simultaneous presence of the multiple facets of a single data point, where each facet provides unique information, will allow a UD unit to represent different phenomena simultaneously. Thus, researchers can examine different research questions with the same UD units based on the concurrent flow of these unique facets. We leverage these two characteristics of UD by conducting big data and text-mining techniques in section 3.3.4 to operationalize our focal constructs.

3.3.3 Data Collection and Preparation

We employ the Python algorithm to trace every individual guest on the Airbnb website who has visited the same host's place at least six times. The reasons we employ "at least six times" as the threshold for re-patronage experiences are twofold. First, we follow the empirical practices presented in HMM studies to build up our CET research framework. Most of these studies leverage 6 datapoints for each observed unit (individuals or firms) to model dynamics (e.g., Ansari, Mela, & Neslin, 2008; Homburg, Steiner & Totzek, 2009; Ngobo, 2017; Zhang et al., 2016). Second, we seek balance in the necessary trade-offs between the total versus individual numbers of datapoints. For example, while reducing the threshold for each individual observed customer from six revisiting experiences to just three will generate many more comments and an increased total number of repeat customers, but it might be challenging to capture individuals' dynamic patterns from just three datapoints from the perspective of algorithmic estimation. Using these two rationales, we develop our dynamics model using active repeat customers who visited the same places at least six times. This generated 3,166 repeat customers' longitudinal comments with 31,736 comments on the Airbnb website during the period 2009-2019. A sample of the raw data is presented in **Table 3.1**, which shows that the reviewer Robert repeatedly visited Denver city and stayed at the same place (listed ID 590 on the Airbnb website), leaving six comments on the website for the same host.

Table 3.1 Sample Raw Data on Airbnb

Listing-ID	city	date	Reviewer-ID	Reviewer Name	comments
590	Denver	2009/4/9	11666	Robert	A great place to stay. Jill is really wonderful. She is very helpful. This location has great access to the public bus.
590	Denver	2009/6/6	11666	Robert	Jill is a wonderful host. Her place is neat and clean. I was very comfortable during my stay. I look forward to staying there again sometime.
590	Denver	2009/10/29	11666	Robert	Jill is a wonderful host. Her home is clean and a great place to relax. I really enjoy hanging out with Jill too. One night she took me to Eton, which was fun and exciting to see that show live. I look forward to staying here again.
590	Denver	2011/1/15	11666	Robert	Another wonderful stay with Jill. I enjoy being in Jill's home and getting to spend time with her. Her home is a warm and comfortable place to be. She has lots of local knowledge about eateries and places to go and things to do. I look forward to staying with her again.
590	Denver	2011/3/28	11666	Robert	I have stayed with Jill before and once again had a great stay. Jill is a wonderful host and a great person. I feel comfortable and rest well here. I will definitely stay with Jill again.
590	Denver	2011/5/15	11666	Robert	I have stayed with Jill before and had another wonderful experience. Jill is the consummate host and always fun and interesting to talk with. I sleep well and feel totally comfortable at her home. Thank you once again Jill.

It is possible to argue that the use of these online reviews/comments potentially renders our dataset liable to inherent bias. This may occur due to (1) reviewers' self-selection and (2) the consequences of predominant positivity, or (3) socially influenced dynamics. We respond to these considerations about bias as follows. First, regarding self-selection bias and the well-known J-shaped (positively skewed, asymmetric, bimodal) distribution of online product reviews, previous empirical results (Hu, Pavlou, & Zhang, 2017) have revealed that even when consumers recognize their self-selection biases, they nevertheless cannot fully account for them due to bounded rationality. We argue that, in this current study, our research goal is not to focus on the influence of online reviews on future ratings, firms' sales revenues, or potential customers' conversion. We are emphasizing the "voice" of repeat customers and aiming to gain insights from many of these voices to capture and optimize CX performance. Thus, the underreporting bias in online reviews (i.e., consumers with extreme ratings, whether positive or negative, are more likely to write reviews) will actually help firms to spot online firestorms/complaints or to highlight positive comments with the aim of attracting potential customers. The research corollary is that this will help scholars to differentiate positive from negative experiences and identify the intervention/treatment effects more obviously.

Secondly, regarding the issue of predominant positivity in online reviews, we argue that this phenomenon is pervasive in the online review realm, not only in our research setting of repeat customers' reviews but also in the context of general, non-repeat customers' reviews. If we examine the valence of the verbatim reviews in our repeat customers' dataset, we find that the average sentiment is 0.96 (range from -1 to +1). This value is consistent with previous findings. For example, Bridges and Vásquez (2018) analyzed reviews of Airbnb from both guests and hosts and found that 93% of Airbnb reviews were positive. Another example can be found in a dataset of 2,686,354 non-repeat, general based customers on Airbnb, which indicates that 98.1% of reviews are positive with only 1.06% being negative (Alsudais & Teubner, 2019). Furthermore, **Table 3.2** demonstrates a stable pattern of positive sensitivities among repeat customers. There is no significant difference in the degree of positive valence across the distinct times of patronage. That is, about 98% of customers' valence are positive, no matter whether the patronage experience is their first or sixth.

Table 3.2 The Distributions of Valences Depending on Times of Patronage

Times of Patronage	Negative Valence	Neutral Valence	Positive Valence
1st time	.8%	.5%	98.8%
2nd time	.5%	.7%	98.8%
3rd time	.7%	.9%	98.4%
4th time	n<10	.8%	98.9%
5th time	.5%	1.3%	98.2%
6th time	.7%	1.1%	98.2%
>6 times	.5%	.8%	98.7%
Average	**.6%**	**.8%**	**98.6%**

For managerial practice, practitioners can only understand/hear their clients' experiences/voices if these have been expressed. Although previous research has consistently identified a positive pattern in online posted ratings (e.g., Chevalier & Mayzlin, 2006; Dellarocas, 2003; Resnick & Zeckauser, 2002), our dataset does not employ the "online numeric ratings" to explore customers' experience. Rather, we extract customers' experience evaluation/perceptions from their verbatim words/true voices.

Thirdly, and in response to considerations that posted comments are subject to influences unrelated to a consumer's objective assessment (such as idiosyncratic errors or social dynamics), we have captured the former effect through accounting for cross-customer heterogeneity in our empirical model (presented in the next section). As regards the effect of social influence (or influences exerted by previously posted comments), previous researchers have found that posted online ratings exhibit systematic patterns over time, and specifically that the valence of ratings tends to decline (Godes & Silva, 2006; Li & Hitt, 2008; Schlosser, 2005). They posit that this trend can be explained by the product or customer life-cycle processes, and an increasing dissatisfaction over time. This can occur because later buyers are reading reviews posted by previous buyers who have dissimilar preferences or because future buyers are less able to assess a growing number of reviews; both of these factors lead to more purchase errors. However, we argue that this phenomenon tends to exist in research settings regarding "pre-purchase" decisions. In practice, "post-purchase" evaluation gives greater weight to the consumer's actual experience with the product/service and, as such, is more strongly influenced by the consumer's independent assessment of the focal service and less influenced by the social factors that influence the "pre-purchase" evaluations. More specifically, this current research focuses on "repeat customers". We argue that previous reviewers' opinions will exert greater influence on infrequent raters than on frequent customers who post multiple reviews of the same service providers.

Lastly, one might raise concerns of endogeneity related to the potential biases induced by endogenous variables, rendering parameters uninterpretable and causal relationships misleading (e.g., Berry, 1994; Villas-Boas & Winer, 1999; Wooldridge, 2010). We argue that our empirical model is a "likelihood function" of the sequence of observed data that makes no causal claims (X attribute leads to Y performance) but rather captures the dynamics of customers' "probabilistic" behaviors in a particular fashion.

There is another reason this paper runs counter to the endogeneity issue. Our research objects are "repeat customers", whose repeating experiences will determinedly be influenced by their own endogenous facets. For example, current perceptions of the CX dimensions influence the current evaluation of the CX performance state, which will further influence later perceptions of the CX dimensions. Thus, endogeneity is less likely to be a significant factor in our research context focusing on repeat customers' CX trajectories. Overall, we conclude that considerations of self-selection, social influence, and endogeneity will not have serious impacts on our empirical results. We acknowledge that there is no perfect practical solution for reconciling all potential issues but we try to balance the trade-offs between methodological sophistication and managerial traceability (Houston, 2016; Lehmann et al., 2011; Rutz &Watson IV, 2019).

3.3.4 Constructs Operationalization: The Text Mining Technique and Dictionary-based Analysis

The rapid emergence and growth of technology capable of analyzing vast amounts of UD through machine learning and other advanced methods (Marr, 2017) has made UD increasingly prominent in the marketing literature (Balducci & Marinova, 2018).The application of big data analytics and text-mining techniques involves the extraction of non-trivial, meaningful knowledge or patterns from unstructured text data. Aggarwal and Zhai (2012) defined text mining as the analysis of data in natural-language texts, serving to process unstructured information and extract meaningful numeric indices from such information, a process that generally involves converting text into numbers (Krallinger, Valencia, & Hirschman, 2008). The numeric indices make information accessible for further analysis or statistical and machine learning algorithms (Meyer et al., 2008; Sebastiani, 2002).

Balducci and Marinova (2018) suggest a three-process framework (sampling-development, measure-analysis, and hypothesis testing) for implementing a UD analysis in marketing research. Berger et al. (2020) propose a four-process procedure, involving (1) preprocessing data, (2) performing a text analysis of the resulting data, (3) converting the text into quantifiable measures and focal constructs in the research, and incorporating the extracted textual information into subsequent modeling and analyses, and then (4) assessing the validity of the extracted text and measures. Each of these steps may vary depending on the research objective. We follow suggestions proposed by Berger et al. (2020) and Balducci and Marinova (2018) concerning the use of qualitative data for quantitative analysis to yield generalizable insights.

After the data collection process has been completed, the next decision to be made concerns the choice of an appropriate research approach for operationalizing the constructs. According to Humphreys and Wang (2017), if the construct is relatively clear, the researcher can use a dictionary to measure it, taking a top-down approach. In principle, a dictionary-based approach is a set of rules for counting concepts based on the presence or absence of a particular word. In a dictionary-based analysis, researchers define and then calculate the measurements that summarize the textual characteristics that represent the construct. For example, in our current study, a compliment can be captured by the frequency of words such as “wonderful stay”, “wonderful place”, and “thrilling experience”. Within dictionary-based approaches, researchers can choose to employ standardized dictionaries or create a custom dictionary. We choose the Linguistic Inquiry

Word Count 2015 Dictionary, which is based on existing psychometrically tested scales, to measure the four dimensions of CX under focus (cognitive, affective, social, and physical-sensorial CX) in response to several word categories in the LIWC dictionary, including affective, social, cognitive, perceptual (see, hear, feel), and biological processes (body). We argue that a dictionary such as LIWC, which bases its measurement on the underlying psychological scales, provides construct validity (Pennebaker et al., 2015; Pennebaker & Francis, 1996; Tausczik & Pennebaker, 2010).

However, in this work, a standardized dictionary was unavailable to measure the constructs representing the CX performance states (referral/recommendation intention, revisit intention, compliment, and complaint) or the six management-related variables that appear on the Airbnb website (accuracy, cleanliness, communication, location, check-in, and value). Thus, it was necessary to create a custom dictionary. We used the processing program WordState (Peladeau, 2016) for this. WordState is software that uses natural language processing techniques to extract (data-mine) words and phrases from the unstructured text data (Berger et al., 2020; Peladeau, 2016).

We created a list of words and phrases and provided it to two experts with doctoral degrees in linguistics to help to develop a customized CX dictionary that would capture the phenomenon of four behavioral variables comprising the CX performance states (revisit intention, referral/recommendation intention, compliment, and complaint), and six management-related variables incorporating the experience evaluation criteria on Airbnb (accuracy, cleanliness, communication, location, check-in, and value). To produce the initial dictionary, the two linguists, working independently, evaluated and conducted a categorization of the relevance of each word/phrase based on a coding schema provided by the researchers. We assessed the inter-rater consistency and found that it exceeded the 0.8 threshold (Rust & Cooil, 1994). We then retained those words/phrases that were consistently evaluated by the linguistic experts as relevant in order to target which concepts to include in the refined dictionary. Two marketing professors were then invited to review the words/phrases that were inconsistently judged by the linguists. By combining the words/phrases that were consistently evaluated by the linguistic experts with the other words/phrases iterated by the marketing professors, we developed the final custom dictionary for the Airbnb experience context. We argue that this dictionary development process provides construct validity for our focal concepts based on Humphreys (2010) and Pennebaker et al. (2015). The dictionary development process, adopted from Berger el al. (2020), Balducci and Marinova (2018), Humphreys and Wang (2017), Pennebaker et al. (2015) as well as Rust and Cooil (1994), is presented in **Figure 3.2.**

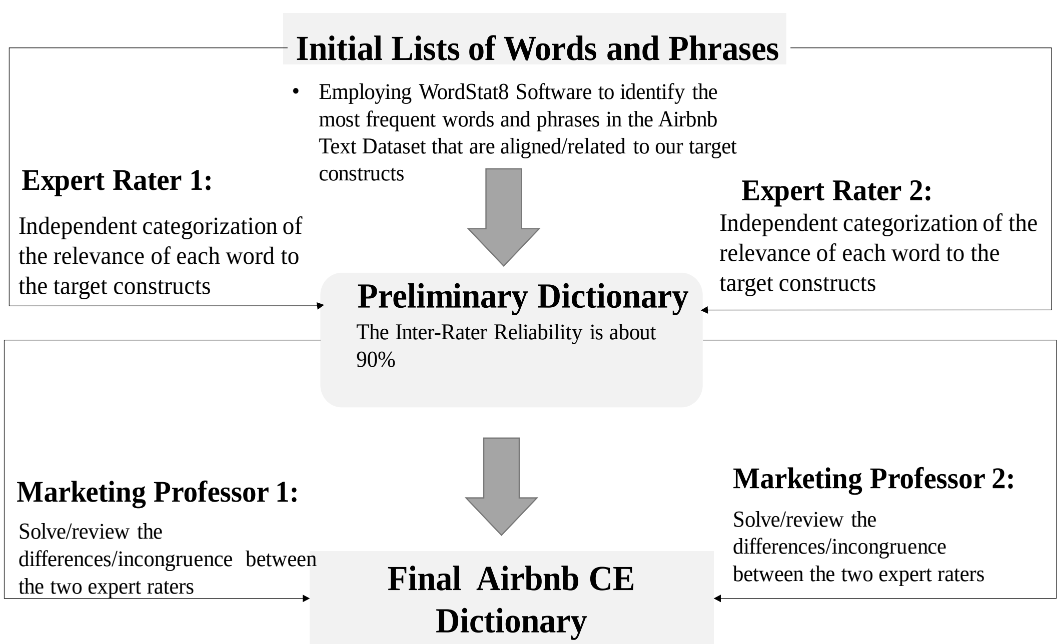


Figure 3.2 Dictionary Development and Validation

We present a sample of the final customized Airbnb Experience Dictionary in **Table 3.3** The Airbnb dictionary encompasses four behavioral variables, presented as "categories" in the dictionary, and the six management-related categories, representing the six experience evaluation criteria on the Airbnb website.

Table 3.3 Examples of the Self-Developed Dictionary

Categories	Sample Words
Consumer Behavioral Categories	
1. Referral	recommend, recommend her place, recommend highly, recommend his place, recommend this apartment, recommended, strongly recommend
2. Revisit	repeat customer, repeat guest, repeat stay, repeat visitor, return, return visit, returning, returning guest, stay as usual, stay here every time
3. Compliment	amazing experience, amazing hospitality, amazing host, amazing stay, apartment is great, apartment is lovely, appreciate, awesome
4. Complaint	annoyed, angry, afraid, disappointed, fearful, hurt, nasty, nervous, sad, tense, worried, worthless, pissed
Management-Related Categories	
1. Accuracy	description, true, able, absolutely, accurate
2. Cleanliness	clean, clean and comfortable, clean and comfy, clean and convenient, clean and modern, clean and neat, clean and quiet, clean and ready
3. Communication	communicate, communication, attention, attention to detail, attentive, attentive host, care, caring
4. Location	easily accessible, easy access, easy to reach, convenient, conveniently, mountain view, parking space, access, accessible, airport, excellent location, good transport links, great location
5. Check-In	book, booked, booking, check, check in, easy check
6. Value	good value for money, great price, great value for money, large room, lots of space, money, plenty of space, price, spend

Furthermore, to integrate the finalized custom dictionary with the standardized dictionary (the default LIWC 2015 Dictionary), we applied a dictionary-based approach using LIWC software to translate unstructured text data into structured numeric data for further analysis (Berger et al., 2020). During operation, the LIWC 2015 software accesses our textual dataset one target word at a time (Pennebaker et al., 2015; Tausczik & Pennebaker, 2010). The process involves searching the dictionary files (the LIWC 2015 Dictionary and the custom Airbnb Experience Dictionary) for a match with the current target word. As target words are identified, the appropriate word category scale is incremented. As the entire original textual dataset is being processed, the counts for the various structural composition elements are also incremented. **Table 3.4** reports the final numeric data, transformed from the sample presented in **Table 3.1.** There are 14 output variables: affective CX; cognitive CX; social CX; physical-sensorial CX; referral/recommendation intention; revisit intention; compliment; complaint; accuracy; cleanliness; communication; location; check-in; and value).

Table 3.4 Example of the Numeric Metrics of the Final Dataset

Listing ID	Visiting_ City	Date	Reviewer ID	Reviewer Name	Referral	Revisit	Compliment	Complaint
590	Denver	2009/4/9	11666	Robert	0	0	14.29	0
590	Denver	2009/6/6	11666	Robert	0	4.76	4.76	0
590	Denver	2009/10/29	11666	Robert	0	2.44	12.2	0
590	Denver	2011/1/15	11666	Robert	0	4.26	6.38	0
590	Denver	2011/3/28	11666	Robert	0	0	12.5	0
590	Denver	2011/5/15	11666	Robert	0	0	7.89	0

Affective_CX	Cognitive_CX	Social_CX	Physical_CX	Accurate	Communication	Cleanliness	Location	Check in	Value
18.18	31.83	18.19	4.55	0	4.76	0	19.05	0	0
11.54	34.61	3.85	15.39	0	0	4.76	0	0	4.76
12.77	23.4	4.26	10.64	0	0	2.44	0	0	0
7.69	25	7.69	11.53	0	0	0	0	0	2.13
16.67	30.56	2.78	11.11	0	0	0	0	0	0
15.38	23.08	7.69	7.68	0	5.26	0	0	0	2.63

3.3.5 Data Overview and Model Free Analysis

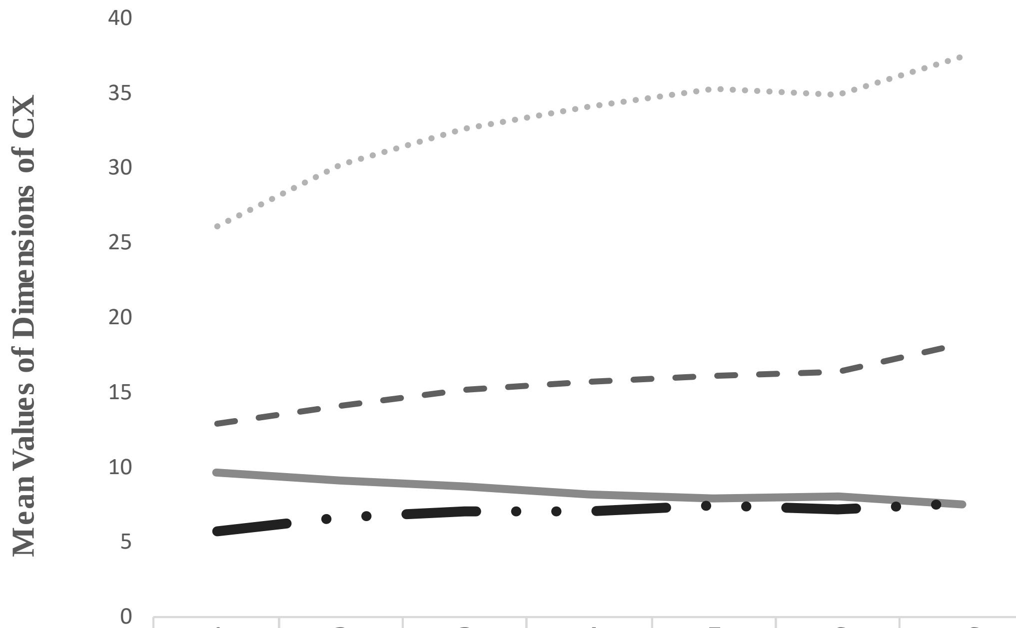
Table 3.5 presents the descriptive statistics and correlation coefficients for the 14 focal variables. Regarding the first four behavioral variables, repeat customers, on average, are more likely to express compliments than intentions to revisit, referrals, or complaints in their comments. Moreover, regarding their four dimensions of experience, repeat customers express more perceptions of cognitive and affective experiences than physical and social elements in their reviews. The correlation coefficients among the variables suggest that they are distinct constructs. Interestingly, customers' affective CX exhibits a high correlation with compliments; this indicates a phenomenon whereby the affective-emotional dimension of CX is dominated by positive emotion, leading to its high association with complementary behaviors. Moreover, most of the variables have significant correlations, which means that the deeper relationships among them can be uncovered through further analysis.

Table 3.5 Data Overview: Descriptive Statistics and Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.Referral	1.00	0.00	-.041**	-.013*	-.049**	-.059**	.264**	-.044**	-0.01	-0.00	-0.00	-.014*	-.016**	-.012*
2.Revisit	0.00	1.00	-.081**	-0.01	-.100**	.064**	-0.01	.075**	-0.01	-.026**	-.025**	-.044**	.030**	-.018**
3.Compliment	-.041**	-.081**	1.00	-.065**	.642**	.441**	-.156**	.130**	-.052**	-.090**	-.051**	-.077**	-.063**	-.090**
4.Complaint	-.013*	-0.01	-.065**	1.00	-.064**	-.029**	0.01	-.018**	0.00	-.019**	-.018**	-.026**	.027**	-0.00
5.Affective CX	-.049**	-.100**	.642**	-.064**	1.00	.399**	-.087**	.045**	-.038**	.043**	-0.01	.024**	-.057**	.045**
6.Cognitive CX	-.059**	.064**	.441**	-.029**	.399**	1.00	-.173**	.240**	-.027**	-.127**	-.085**	.049**	-.014*	-.084**
7.Social CX	.264**	-0.01	-.156**	0.01	-.087**	-.173**	1.00	-.057**	-.013*	.260**	-0.01	-.014*	-0.01	0.00
8.Physical CX	-.044**	.075**	.130**	-.018**	.045**	.240**	-.057**	1.00	-.018**	-.069**	-.049**	-.071**	-.029**	-.026**
9.Accurate	-0.01	-0.01	-.052**	0.00	-.038**	-.027**	-.013*	-.018**	1.00	0.01	-0.00	-.014*	.092**	-.014*
10.Communication	-0.00	-.026**	-.090**	-.019**	.043**	-.127**	.260**	-.069**	0.01	1.00	.047**	.015**	-0.00	.020**
11.Cleanliness	-0.00	-.025**	-.051**	-.018**	-0.01	-.085**	-0.01	-.049**	-0.00	.047**	1.00	.044**	-0.01	.104**
12.Location	-.014*	-.044**	-.077**	-.026**	.024**	.049**	-.014*	-.071**	-.014*	.015**	.044**	1.00	-0.01	.053**
13.Check-In	-.016**	.030**	-.063**	.027**	-.057**	-.014*	-0.01	-.029**	.092**	-0.00	-0.01	-0.01	1.00	-0.01
14.Value	-.012*	-.018**	-.090**	-0.00	.045**	-.084**	0.00	-.026**	-.014*	.020**	.104**	.053**	-0.01	1.00
Mean	0.93	1.10	15.07	0.20	16.31	34.27	8.14	7.13	0.19	1.96	1.04	2.67	0.22	1.16
S.D	4.13	3.61	20.38	1.35	15.27	23.76	10.80	7.96	1.33	5.18	4.33	6.45	1.31	3.81
Range	100	100	100	100	100	200	200	100	50	100	100	100	50	100

Note: * denotes significance at the 5% and ** significance at the 1% levels

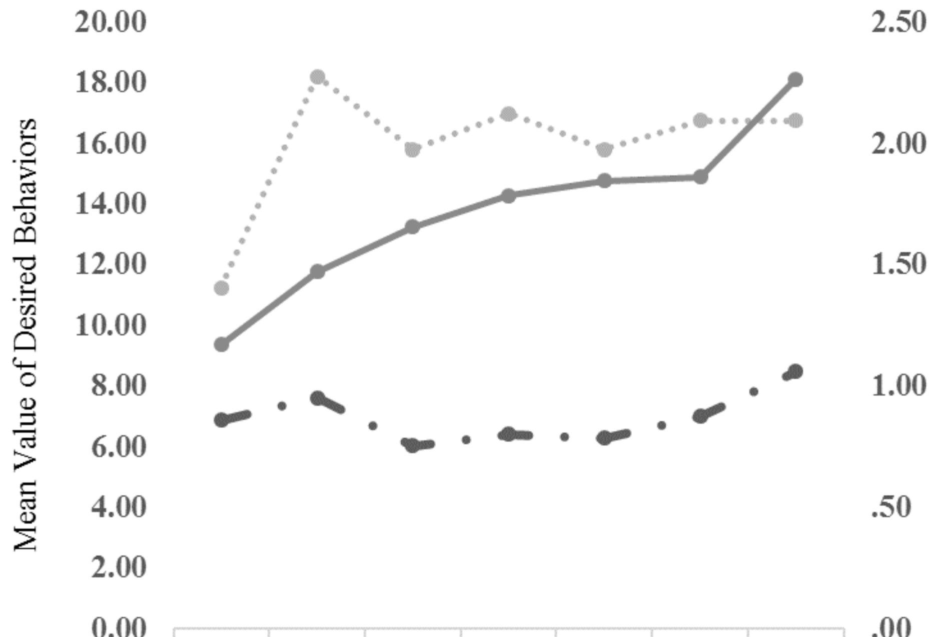
We depict the general trends in the data in **Figures 3.3 to 3.5**.



Revisiting Occasions	1	2	3	4	5	6	>6
Affective_CX	13	14	15	16	16	16	18
Social_CX	9.57	9.03	8.75	8.20	7.90	7.96	7.50
Physical_CX	5.69	6.64	7.05	7.05	7.40	7.09	7.59
Cognitive_CX	26.08	30.25	32.64	34.08	35.28	34.96	37.43

Figure 3.3 Trends in the Four Dimensions of Customer Experience Perceived by Repeat Customers

Figure 3.3 presents the trends in the average score for the four dimensions of CX over six repeat service encounters. The trends of affective, physical, and cognitive CXs show patterns of increase; however, the average score for Social_CX indicates a declining trend. Overall, repeat customers show a relatively steady and upward movement in their affective, physical, and cognitive dimensions of experiences. The observed upward and downward trends in CX indicate that the development of repeat customers' experience trajectories is not static but dynamic, fluctuating during their six repeat service encounters.



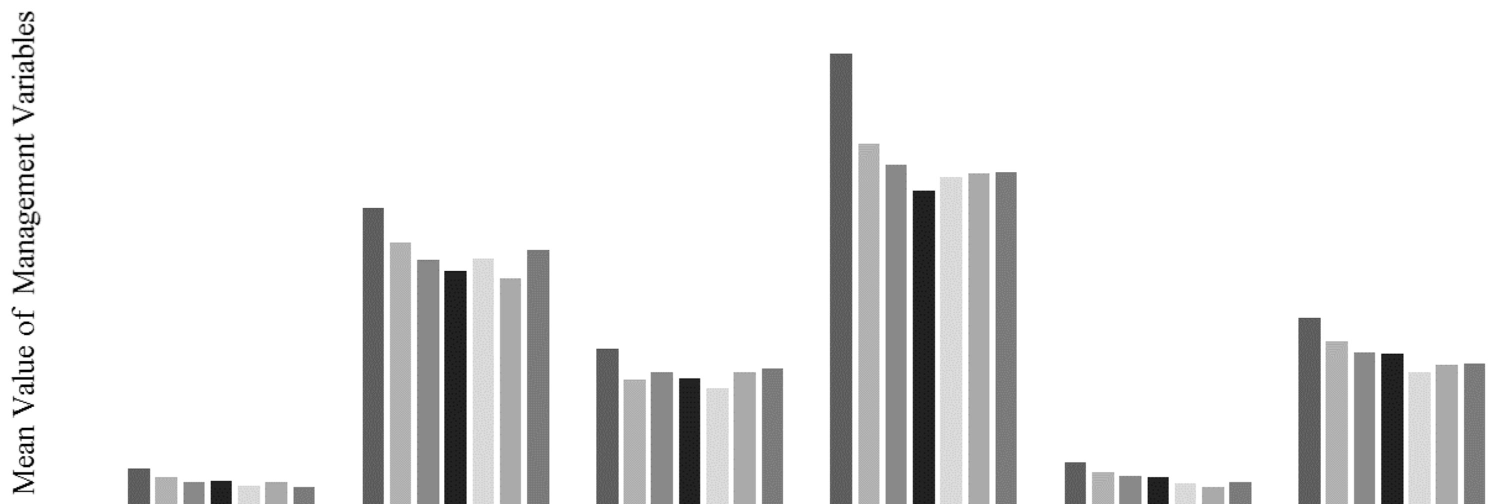
Mean Value of	Revisiting Occasions						
	1	2	3	4	5	6	>6
Revisit	.55	1.32	1.22	1.32	1.19	1.22	1.04
Referral	.86	.95	.75	.80	.79	.88	1.06
Compliment	9.36	11.78	13.25	14.28	14.76	14.91	18.13

Figure 3.4 Trends in the Average Score for the Three Customer Behaviors Desirable to Managers

Figure 3.4 presents the trends in three positive behavioral variables; namely, revisit intention, referral intention, and compliments. Generally, the three behavioral variables exhibit upward development over the six repeat service occasions. The figure suggests a (relatively significant) increasing trend in the average score of compliments but more fluctuations for revisit and referral intentions.

However, the six management-related variables (the six experience evaluating criteria from the Airbnb website) show different patterns over the six revisit occasions in **Figure 3.5**. Generally, all of them show a declining trend with different levels of fluctuations. **Figure 3.5** uses a histogram to present the heterogeneity of the six management-related variables for the six repeat service experiences about which customers experienced and expressed their evaluations in their comments. For the experience providers, viewing the downward patterns in these six variables can help them to rethink the perceived quality/sustainability of their service provision or even the validity of using these six criteria to evaluate their service.

Several questions arise from **Figures 3.3-3.5**. Can we disentangle from the data the dynamics of CX, desirable consumer behaviors, and management strategies? How will the four dimensions of CX and the six management-related variables influence repeat customers' desired behaviors? Do these migration mechanisms have primarily short- or long-term effects? Could the experience providers develop "customized" strategies to optimize their repeat customers' experience? We will answer these questions in the following sections.



	Accurate	Communication	Cleanliness	Location	Check-In	Value
Revisit Times 1	.29	2.29	1.22	3.48	.34	1.45
Revisit Times 2	.23	2.03	.98	2.79	.27	1.28
Revisit Times 3	.19	1.90	1.04	2.63	.24	1.19
Revisit Times 4	.19	1.81	.98	2.43	.23	1.17
Revisit Times 5	.16	1.90	.91	2.54	.18	1.03
Revisit Times 6	.19	1.75	1.04	2.56	.16	1.09
Revisit Times >6	.15	1.98	1.06	2.57	.19	1.11

Figure 3.5 Trends in Six Management-Related Variables Perceived by Repeat Customers

3.4 Empirical Analysis

3.4.1 Empirical Model Specification

We develop a dynamic model following Netzer et al. (2008) and Zhang et al. (2016) based on the evolution of the CX performance states and assess the impact of distinct dimensions of perceived CX and perceived managerial actions on CX performance states. In the research model depicted in **Figure 3.1**, the latent states are a finite set of CX performance states. The transitions between the states are determined by a set of time-varying covariates (the physical-sensorial, cognitive-rational, affective-emotional, and social-relational dimensions of CX) or other managerial related variables, leading to a nonhomogeneous HMM. The state-dependent distribution is defined by a dependency between the latent/hidden CX performance states and the likelihood of repeat customers expressing revisit intentions, referral intentions, compliments, and complaints. The number of latent states is determined by the complexity of the relationship and its dynamics over time. To account for cross-customer heterogeneity, we employ the latent class approach to distinguish between relationship-state dependence and zero-order heterogeneity (Kamakura & Russell, 1989).

Using the multivariate HMM, we empirically infer the latent CX performance states from the time-varying levels of each repeat customer's expression of four consumer behavioral variables. The vector of CET state variables for customer I at time j is $Y_{ij} =$ ($Revisit_{ij}$, $Referral_{ij}$, $Compliment_{ij}$, $Complaint_{ij}$). The latent CX performance state at time j for customer i has four components: (1) the initial latent state probability π_i, which represents the repeat customer's initial state; (2) a matrix of transition probabilities among states that explains how the repeat customers move from one CET state to the next, as well as the effects of various migration strategies on this transition; (3) a multivariate likelihood of interrelated state variables, conditional on the CX performance state $L_{ij|s}$= f_{is} ($Revisit_{i,j}$, $Referral_{i,j}$, $Compliment_{i,j}$, $Complaint_{i,j}$); and (4) the repeat customer's latent CX performance state probability during each time period.

(1) Initial state distribution. Let s denote a latent CX performance state (s=1,2,3,4,….. S) and π_{is} the probability that customer i is in state s during the first period of our dataset, where $\Sigma_{s=1}^{S}\pi_{is}=1$.

(2) Markov chain transition matrix. The HMM transition matrix $\Omega_{i,j-1\rightarrow j}$ denotes the probability that a repeat customer will migrate from one state to each other state over six periods, modeled as a Markov process.

$$
\begin{array}{ccccccc}
 & \textit{State} \text{ at t} & & & & & \\
\text{State at t-1} & 1 & 2 & 3 & \ldots & S-1 & S \\
1 & W_{ij1,1} & W_{ij1,2} & W_{ij1,3} & \ldots & W_{ij1,S-1} & W_{ij1,S} \\
2 & W_{ij2,1} & W_{ij2,2} & W_{ij2,3} & \ldots & W_{ij2,S-1} & W_{ij2,S} \\
3 & W_{ij3,1} & W_{ij3,2} & W_{ij3,3} & \ldots & W_{ij3,S-1} & W_{ij3,S} \\
. & . & . & . & & . & . \\
. & . & . & . & \ldots & . & . \\
. & . & . & . & & . & . \\
S-1 & W_{ijS-1,1} & W_{ijS-1,2} & W_{ijS-1,3} & \ldots & W_{ijS-1,S-1} & W_{ijS-1,S} \\
S & W_{ijS,1} & W_{ijS,2} & W_{ijS,3} & \ldots & W_{ijS,S-1} & W_{ijS,S}
\end{array}
$$

$W_{ijss'}$=P($S_{ij} = s' \mid S_{ij-1} = s$) is the conditional probability that a customer will move from state s at time j-1 to state s´ at time j and $\forall s, s'$, $\Sigma_{s'} W_{ijss'} = 1$. These transition probabilities might be influenced by the migration mechanisms (four CX variables, six management-related variables) at time j-1. We define each transition's probability as a function of the migration mechanisms using a logit specification to ensure that $0 \leq W_{ijss'} \leq 1$. That is, $W_{ijss'} = \frac{e^{X_{ij-1}'\gamma_s}}{1+\Sigma_{s=1}^{S-1} e^{X_{ij-1}'\gamma_s}}$, where X_{ij-1} is a vector of the migration mechanisms affecting the transition between CX performance states and γ_s is a state-specific vector of the response parameters that measure the impact of each migration mechanism on the transition probability $W_{ijss'}$. In our transition matrix specification, we include all possible migration mechanisms (10 variables in total) to compare the relative effects of all migration strategies for each migration path and identify the most effective strategy for each path.

(3) HMM likelihood function. Conditional on being in state s at time j, it is an expression of a repeat customer's level of referral, revisit intention, compliment, and complaint. These four indices are unconditionally interrelated. If repeat customer i at time j is in a latent CX performance state S_{ij}=s, we can factor the conditional discrete-continuous joint likelihood using the multivariate normal distribution to model the joint distributions on all three variables as follows: $L_{ij|s}=f_{is}(Referral_{ij}, Revisit_{ij}, Compliment_{ij}, Complaint_{ij})$. Considering the Markovian structure of the model, the likelihood of observing a set of joint customer expressions at time j depends on all expressions prior to that event. The likelihood of a repeat customer's response over J periods is $L_{ij}=P(Y_{i1}=y_{i1}, Y_{i2}=y_{i2}, Y_{i3}=y_{i3},\ldots\ldots Y_{iJ} = y_{iJ})=\pi_i M_{i1} \Omega_{i,1\rightarrow 2} M_{i2} \ldots\ldots \Omega_{i,J-1\rightarrow T} M_{iJ}\ 1'$, where π_i is the initial state distribution, Ω is the transition matrix, M is an $S\times S$ diagonal matrix with the elements $L_{ij|s}$ on the diagonal and $1'$ is an $S\times 1$ vector of ones.

(4) Latent state probability (the state membership distribution). We use a filtering approach to determine the probability that repeat customer i is in state s at time j, conditional on this customer's history as $P(S_{ij}=s|\ Y_{i1}, Y_{i2}, Y_{i3},\ldots\ldots Y_{iJ}) = \pi_i M_{i1} \Omega_{i1\rightarrow 2} M_{i2} \ldots\ldots \Omega_{i,j-1\rightarrow t\cdot s} L_{ij|s}\ / L_{ij}$, where $\Omega_{i,j-1\rightarrow j\cdot s}$ is the s^{th} column of the

transition matrix and L_{ij} is the likelihood of the sequence of joint state variables up to time j.

In our HMM, the latent CX performance states are determined not only by each customer's time-varying levels of behaviors but also by the time-varying levels of his or her perceptions of the different dimensions of CX and six Airbnb experience evaluation criteria. Thus, we suppose that the multiple dimensions of CX and six experience evaluation criteria will exert both short- and long-term effects on the desired CBs. The former will influence the identification of the CX performance states, while the latter will influence the migration paths.

For the estimation, we use the software program Latent Gold 5.1 (Vermunt & Magidson, 2015), which applies a special variant of the EM algorithm called the forward-backward or Baum-Welch algorithm. We employ Latent Gold to estimate an HMM characterized as nonhomogeneous (integrating covariates in the transition probability matrix) and heterogeneous (capturing cross-customer heterogeneity). We allow for cross-customer heterogeneity in the model parameters only in the transition probability matrix and initial state distribution, and not in the state-dependent distribution. Our rationale for this (Kamakura & Russell, 1989; Netzer et al., 2018; Train, 2009) being that we wish to allow for different customers having different levels of stickiness to the states but assume that, given a CX performance state, all customers have the same structure, exhibit similar behaviors, or respond in a similar manner to management actions. The attractiveness of such an approach lies in the increased ease of interpreting the CX performance states because they mean the same thing to all customers. On the other hand, allowing for cross-customer heterogeneity in the state-dependent distribution implies that a "higher state" for one customer may be very different from a “higher state” for another. In addition, we include the four dimensions of CX and six management-related variables (which the experience providers can control) in the transition matrix, such that repeat customers’ responses to their staying experiences and managerial actions will have a long-term effect on repeat customers’ behaviors and the migration across the latent CX performance states.

To build an HMM in Latent Gold, the observed variables Y_{it} (in our case, these are revisit intention, referral intention, positive compliment, and negative complaint) must be selected as the indicators. Next, the state-dependent distribution that corresponds to the indicator variables as covariates is selected. The covariate variables comprise four CX variables (the cognitive, affective, physical, and social dimensions) and six experience-evaluating criteria/management-related variables (e.g., accuracy, cleanliness). We include the covariates X_{it} that have impacts on both the transition probabilities and the state-dependent distribution. When covariates are included in the transition probabilities, they are postulated to create a regime shift in CB and exert a long-term effect, whereas the covariates included in the state-dependent distribution affect CB only in the current time period and therefore have a short-term impact. We include the ten covariates in both the transition probability matrix and state-dependent distributions to investigate their effects on short-/long-term CBs and the formation of the CET.

3.4.2 Empirical Results

In our HMM, the latent CX performance states are determined by each repeat customer’s time-varying levels of four behavioral variables (referral, revisit, compliments, complaints). The HMM simultaneously identifies the number of CX performance states and the number of customer segments in **Table 3.6**. In **Table 3.7**, we discuss the characteristics of the distinct states and repeat customer segments, as empirically identified by the model. In **Table 3.8**, we present the identified migration paths among distinct CX performance states for different repeat customer segments. Following this, we include the ten covariate variables (four dimensions of CX and six management strategies) in the state-dependent distribution, assuming that they have only a short-term impact on the four behavioral variables. Later, we extend that model and include ten covariates in the transition probability matrix to investigate their effects on long-term migration behavior. In **Table 3.9**, we express the short-term impact of ten managerial related variables on the CX performance states and **Table 3.10-3.11** depicts the long-term impacts of ten managerial variables on the migration of the CX performance states for different customer segments. Finally, **Table 3.12** is presented to quantify the marginal effect of the significant variables found in **Tables 3.10** and **Table 3.11** so as to understand the performance consequences of applying migration strategies.

3.4.2.1 Choosing the Number of States

We lack any *a priori* knowledge about the exact number of CX performance states. To estimate the number of states, we adopt several model selection criteria from the literature. Our selection criteria include the log-likelihood, the commonly used Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Singh et al., 2011; Yan & Tan, 2014), and the Consistent Akaike Information criterion (CAIC) (Netzer et al., 2017). Given a set of candidate models for the data, the preferred model is the one with the lowest value of the selection criteria. The lower the BIC and CAIC values, the better fitting and more parsimonious the model. Obviously, the final decision depends upon the interpretability of the dynamic latent states, latent classes, and their sizes. The models were fitted with an increasing number of states and classes, ranging from one to five. The results (presented in **Table 3.6**) suggest that a 3-state, 2-class model fits the data better than the other specifications.

Table 3.6 Model Selection

Model Alternatives	LL	BIC(LL)	AIC(LL)	AIC3(LL)	CAIC(LL)
2-State 2-Class	- 66,235.91	132,842.59	132,563.81	132,609.81	132,888.59
3-State 2-Class	**40,750.15**	**-81,169.83**	**- 81,418.30**	**- 81,377.30**	**- 81,128.83**
4-State 2-Class	67,425.04	- 134,342.29	- 134,724.09	- 134,661.09	- 134,279.29
5-State 2-Class	87,022.94	- 173,328.52	- 173,867.88	- 173,778.88	-173,239.52

3.4.2.2 The Identified CX Performance States and Repeat Customer Segmentation

As we report in **Table 3.7**, significantly different mixtures of state variables (four consumer behavior outcomes) arise for the three CX performance states. In **Table 3.8**, which presents the migration path probability matrix, the diagonal represents the mean probability of remaining in the same state (stickiness), while the off-diagonal values indicate the probabilities that a repeat customer in a given CX performance state will migrate to a different one. As presented in **Table 3.7**, we identify three hidden states: (1) the Neutral (N) state with the lowest summative score of the desired behavioral variables (revisit, referral, compliment) and the highest complaint score; (2) the Positive-Active (P-A) state with a medium score for compliment but higher scores for referral and revisit performance; and (3) the Positive-Passive (P-P) state with the highest score for compliments but lower scores for referral and revisit performances compared with P-A state. Moreover, the result for the latent class approach that was used to capture the unobserved cross-customer heterogeneity in HMM contains two segments. As indicated in **Table 3.7**, we identified two segments: (1) a more complimentary with lower engagement group, which has a lower level of engagement (e.g., expression of revisit, referral, and complaint) but more complimentary words (a higher compliment score), and (2) a less complimentary with higher engagement group, which scores high on expressions of revisit, referral, and complaint but has fewer kind words (a lower compliment score). These are estimated to represent 54% and 46% of the repeat customers, respectively. As we only included heterogeneity in the transition probability matrix, we obtain two estimated transition probability matrices, one for each group (presented in **Table 3.8**).

The initial state probabilities of being in CX performance state N, P-A, or P-P for Group 1 are 6%, 19%, and 75%, while they are 10%, 43%, and 47% for Group 2. Hence, although a repeat customer tends to begin in a positive-passive (P-P) state for both groups, 6% of Group 1 and 10% of Group 2 start in the N state while 19% of Group 1 and 43% of Group 2 start in the P-A state. This confirms the importance of studying how to encourage customers to remain in P-A/P-P states and how to motivate them to migrate from N to P-A/P-P states.

Table 3.7 CX Performance States Identification and Repeat Customer Segmentation

	CX Performance States			Repeat Customer Segmentation	
State Name and Customer Segment	Neutral (N) State	Positive-Active (P-A) State	Positive-Passive (P-P) State	Group 1 More Complimentary with Lower Engagement	Group 2 Less Complimentary with Higher Engagement
Size	5.09%	25.63%	69.28%	54.48%	45.52%
(1) Referral (mean)	0.51	3.58	0.00	0.44	1.55
(2) Revisit (mean)	1.08	4.18	0.00	0.53	1.84
(3) Compliment (mean)	5.26	8.18	19.46	17.66	13.68
(4) Complaint (mean)	4.14	0.00	0.00	0.14	0.30
Total Score =(1)+(2)+(3)-(4)	**2.71**	**15.94**	**19.46**	**18.48**	**16.78**

3.4.2.3 Transition across the CX Performance States in the Two Segments

Repeat customers belonging to different segments express distinct CX performances. In **Table 3.8,** the most likely destination for Group 1 (more complimentary with lower engagement) is P-P state. For Group 2, the most likely destination is P-A state. We find that when the repeat customers in Group 1 move to N or P-A state, they are more likely to return to P-P state. We also find that the less complimentary with higher engagement group (Group 2) tends to end up in P-A state. They also are more likely to move down from their first trajectory state to a lower state than are the members of Group 1. However, we suggest that repeat consumers in Group 2, with a higher level of engagement, present valuable signals for managers since this segment devotes more efforts to recruiting new clients through referrals and recommendations, and expresses strong intentions to revisit the experience provider. This means that experience providers should pay attention to this segment by listening to their complaints and attempting to switch them from N state (with the highest complaint score) to P-A or P-P state (with a zero-complaint score).

Table 3.8 Initial State Probability and Transition Probability Matrices of the Two Groups

Customer Segment	**Move from a Previous State**	**To Next State** Neutral (N) State	Positive-Active (P-A) State	Positive-Passive (P-P) State
Group1: More Compliment with Lower Engagement	Neutral State	0.20	0.13	0.67
	Positive-Active State	0.10	0.36	0.54
	Positive-Passive State	0.05	0.12	0.83
Group 2: Less Compliment with Higher Engagement	Neutral State	0.34	0.45	0.21
	Positive-Active State	0.32	0.53	0.15
	Positive-Passive State	0.27	0.55	0.18
Initial State Probability		**N State**	**P-A State**	**P-P State**
Group 1 (More Compliments with Lower Engagement)		0.06	0.19	0.75
Group 2 (Less Compliments with Higher Engagement)		0.10	0.43	0.47

The following two sections (3.4.2.4 and 3.4.2.5) present the effectiveness of short-term effects and long-term effects exerted by the four CX dimensions and six managerial variables. In this paper, we examine four CX dimensions and six management variables perceived by repeat customers, working as covariates in both the state-dependent distribution and the transition matrix. Covariates that are included in the state-dependent distribution, by definition, affect the customer behavior only in the current time period and therefore have short-term effects. Covariates that are included in the transition matrix, on the other hand, are postulated to have long-term effects on the customer's behavior. The rationale being that these covariates create a regime shift in customer behavior by transitioning the customer to a different state.

3.4.2.4 The State-Dependent/Short-Term Effects of the CX Dimensions and Managerial Variables

In **Table 3.9**, the constant vectors (intercepts) of the three CX performance states are -0.87, 0.17, and 0.71 for the N, P-A and P-P states respectively (all significant at the 1% level). The relatively large distances between the states indicate that the states are well-identified.

We first discuss the results regarding the short-term effects of the multiple dimensions of CX on customers' formation of the three CX performance states. First, the coefficients of the affective-emotional CX are -0.043, -0.015, and 0.058 for states N, P-A, and P-P respectively (all significant at the 1% level). The positive coefficient of state P-P suggests that the more affective the experience, the higher the CET state. Additionally, the decreasing magnitude of the coefficients shows that as repeat customers move from

P-P to P-A to N, they become less responsive to increases in affective experience. Second, the coefficients of the cognitive-rational CX are -0.001 (nonsignificant), 0.004 (significant at 1%), and -0.003 (significant at 1%) for N, P-A, and P-P states respectively. The negative coefficient of state P-P suggests that the greater the cognitive experience, the less likely the customer is to be in P-P state. However, the positive coefficient of P-A state suggests that the greater the cognitive CX, the greater the likelihood of being in P-A state. Third, the coefficients of social-relational CX are 0.009, 0.016, and -0.025 (all significant at 1%) for states N, P-A and P-P respectively. The negative coefficient of state P-P suggests that the greater the social experience, the lower the likelihood of being in state P-P. In contrast, the positive coefficients of N and P-A states suggest that the greater the social-relational dimension of CX, the higher the probability of being in these two states. Fourth, the coefficients of the physical-sensory CX are -0.011 (significant at 1%), 0.008 (significant at 1%), and 0.004 (nonsignificant) for states N, P-A, and P-P respectively. The physical CX does not exert a significant influence on P-P state. The positive coefficient of state P-A suggests that the greater the physical-sensory experience, the greater the likelihood of being in P-A state. However, the negative coefficient of N state suggests that the greater the physical-sensory dimension of CX, the lower the probability of being in N state.

Comparing the coefficients of two CX performance states, P-P and P-A, we find that affective CX has a positive relationship with P-P state (0.058, significant at 1%) but a negative one with P-A state (-0.015, significant at 1%). Interestingly, both cognitive and social CXs have a negative relationship with P-P state (-0.003 and -0.025, both are significant at 1%) but a positive one with P-A state (0.004 and 0.006, both are significant at 1%). We suggest that repeat customers in P-A state have a higher expression of revisit and referral intention than those in P-P state, which requires stronger responses to the cognitive elements (through the thinking process) and social elements (through the social process) of their staying experiences. Moreover, affective CX has a positive relationship with P-P state (0.058, significant at 1%) but a negative one with P-A state (-0.015, significant at 1%). We suggest that repeat customers in P-P state express more compliments than those in P-A state, which implies that the P-P state requires stronger responses of affective components (e.g., positive emotions). Finally, we find that the less affective and physical the CXs, the greater the likelihood of being in N state (-0.043 and -0.011, both are significant at 1%), where consumers will complain about their dissatisfactory experiences through a social process, reflected by the positive relationship with the social components of their staying experiences (0.009, significant at 1%).

Two points are worth noting regarding the estimated effects of dimensions of CX on state-dependent distributions. First, to have a short-term impact on repeat customers' highest CX performances state (P-P) in the current period, increasing affective dimension of CX is suggested. On the other hand, to have a significantly short-term effects on P-A state in the current period, increasing repeat customers' perceptions of the other three dimensions of CX (cognitive, social, physical CXs) are suggested. Second, regarding the managerial related variables (the six evaluation criteria on Airbnb), to have a short-term impact on repeat customers' CX performance (P-P) state in the current period, it is suggested that providers increase the perceived quality of communication, cleanliness, and convenience of location in the current period.

Table 3.9 State-Dependent Distribution Parameters for Each State: The Short-Term Effects of Covariates in the Current Time Period

CX Performance State	Neutral (N) State			Positive-Active (P-A) State			Positive-Passive (P-P) State		
Covariates	**Parameter**	**s.e.**	**z-value**	**Parameter**	**s.e.**	**z-value**	**Parameter**	**s.e.**	**z-value**
Four Dimensions of Customer Experience									
1. Affective-Emotional	-0.043***	0.005	-8.762	-0.015***	0.003	-5.148	0.058***	0.003	23.096
2. Cognitive-Rational	-0.001	0.002	-0.277	0.004***	0.001	3.552	-0.003***	0.001	-3.776
3. Social-Relational	0.009 ***	0.003	3.578	0.016***	0.002	10.277	-0.025***	0.001	-18.577
4. Physical-Sensory	-0.011***	0.005	-2.501	0.008***	0.003	2.810	0.004	0.002	1.535
Six Experience Evaluating Criteria Controllable and Manageable by Experience Providers									
1. Accurate	0.008	0.019	0.396	-0.003	0.012	-0.217	-0.005	0.010	-0.486
2. Communication	-0.014*	0.008	-1.891	-0.002	0.004	-0.502	0.017***	0.004	4.169
3. Cleanliness	-0.041***	0.013	-3.119	0.012*	0.007	1.648	0.029***	0.007	4.192
4. Location	-0.016***	0.007	-2.521	0.003	0.004	0.867	0.013***	0.003	3.808
5. Check-in	0.033***	0.011	2.915	-0.012	0.009	-1.390	-0.021***	0.007	-3.137
6. Value	0.006	0.009	0.648	0.005	0.006	0.922	-0.011***	0.004	-2.576

Note: * significant at 10%   ** significant at 5%   *** significant at 1%

For the management-related variables—the six experience evaluating criteria on the Airbnb website that the experience providers can control—we find positive relationships between communication (0.017), cleanliness (0.029), and location (0.013) and P-P state (all significant at 1%) but negative relationships between check-in (-0.021) and value (-0.011) and P-P state (all significant at 1%). The negative coefficients in P-P state suggest that the more prolonged the check-in process, the lower the likelihood of being in P-P state, and that the higher the price, the lower the probability of being in P-P state in terms of compliment expression. In contrast, we find negative relationships between communication (-0.014, significant at 10%), cleanliness (-0.041, significant at 1%), and location (-0.016, significant at 1%) and N state but a positive relationship between check-in (0.033, significant at 1%) and N state. The negative coefficients in N state suggest that the lower the quality of the communication, cleanliness, and convenience of the host/location, the greater the probability of being in N state, represented by the highest complaint score and the lowest desired behavioral score. Moreover, the positive coefficient in N state confirms that the longer the check-in process, the higher the probability of being in N state.

3.4.2.5 The Long-Term/Migration Effects of CX Dimensions and Managerial Variables

Tables 3.10 and **3.11** report the effectiveness of the CET migration strategies for the two groups identified previously. **Table 3.10** presents the parameter estimates of the migration mechanisms across four paths for Group 1, including two upward migration paths (from N state to P-A state and from N to P-P state) and two downward migration paths (from P-A state to N state and from P-P state to N state). We argue that a firm will have the managerial objectives of increasing the probabilities of upward migration (the promotion objective) and decreasing the probabilities of downward migration (the prevention objection). We employ the migration mechanisms (the four dimensions of CX or the six management variables) to achieve the above managerial objectives. We call the mechanisms that are useful for increasing the likelihood of upward migration the Promotion strategies, and the mechanisms that are effective at decreasing the probabilities of downward migration the Prevention strategies.

The first two paths show how the probability of advancing the customers' CET from a lower state to a higher one (N→P-A, N→P-P) has increased to satisfy the firm's promotion objective. The last two paths show how the probability of preventing the customers' CET level from degrading to a lower state (P-A→N, P-P→N), satisfying the firm's prevention objective. This comparison allows us to highlight the valid variables or strategies for two purposes: promotion and prevention. The values shown in bold in the table indicate strategies that are statistically significant; the gray-shaded values indicate the variables that "backfire," having the opposite result from the intended strategic purpose.

Table 3.10 Transition Probability Parameters: The Long-Term Effects of Migration Mechanisms for Group 1

Group1: More Compliments with Lower Engagement	**Increasing the Probability of Upward Migration from N State to P-A/P-P States (Positive Coefficients Expected)**		**Decreasing the Probability of Downward Migration from P-A/P-P States to N State (Negative Coefficients Expected)**	
Mechanism 1	**From N to P-A State**	**Form N to P-P State**	**From P-A to N State**	**From P-P to N State**
Affective CX	-0.01 (0.04)	**0.08***** **(0.03)**	-0.02 (0.63)	**-0.08***** **(0.01)**
Cognitive CX	0.00 (0.02)	-0.02 (0.01)	-0.00 (0.02)	0.00 (0.01)
Social CX	0.04 (0.03)	0.01 (0.03)	0.00 (0.02)	**0.03***** **(0.01)**
Physical CX	0.04 (0.06)	0.02 (0.05)	-0.01 (0.04)	-0.00 (0.01)
Mechanism 2	**From N to P-A State**	**Form N to P-P State**	**From P-A to N State**	**From P-P to N State**
Accuracy	1.25 (11.38)	1.18 (11.43)	0.01 (0.35)	0.03 (0.07)
Communication	-0.03 (0.05)	0.04 (0.04)	-0.05 (0.04)	-0.05 (0.03)
Cleanliness	-0.08 (0.26)	-0.05 (0.13)	0.01 (0.06)	-0.07 (0.05)
Location	-0.02 (0.08)	0.02 (0.05)	-0.00 (0.06)	-0.03 (0.02)
Check-In	-0.11 (0.37)	-0.04 (0.21)	-0.04 (0.15)	**0.06**** **(0.03)**
Value	0.02 (0.14)	-0.01 (0.12)	-0.01 (0.1)	0.01 (0.03)

Note: ** significant at 5%; *** significant at 1%

Overall, the repeat customers in Group 1 (people who expressed more compliments with lower engagement) seem to benefit from the migration mechanism through an affective-emotional experience. The affective CX not only increases the probability of shifting up but also reduces the likelihood of moving down. Specifically, for Group 1 repeat customers in N state, the more affective the CX, the higher the probability of transferring to P-P state (0.08, significant at 1%). Moreover, for the same group in P-P state, the more affective the CX, the lower the likelihood of declining to N state (-0.08, significant at 1%). For repeat customers in Group 1, social CX and the check-in process seem to backfire, as they exert the opposite effect on the desired transitional direction. Our results show that, for people in Group 1, the social dimension of CX will increase the probability of downward migration from P-P state to N state (0.03, significant at 1%). Generally, for Group 1, whose potential destination is the P-P state, increasing their perception of affective CX is most efficient way to manage their CX performances. On the other hand, mechanism 2 (i.e., the six evaluation criteria on Airbnb website) is not as effective a migration toolkit for managers wishing to boost the upward migration or mitigate the downward switch for this group. **Figure 3.6** depicts the directions that can be used to identify how to deploy the relevant migration strategies, given the CX performance states for the first segment of repeat customers. Drawing on our empirical results from **Table 3.10**, the promotion strategies describe the most efficient tactics to trigger positive state change (from N to P-P/P-A states); the preventive strategies indicate the most efficient tools for preventing negative state change (from P-P/P-A states to N state).

The Effectiveness of Migration Mechanisms on Group1 (Size=54.48%): More Compliments with Lower Engagement

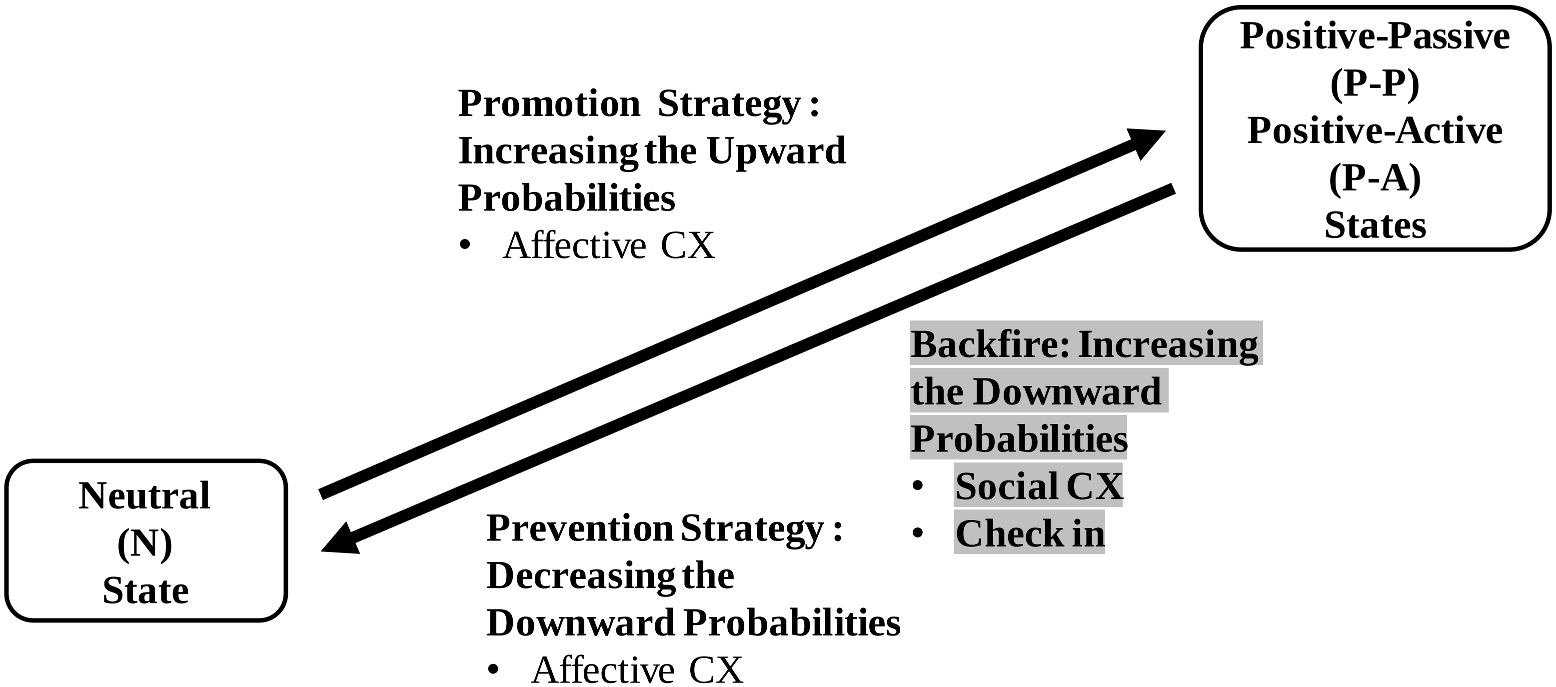


Figure 3.6 The Effective Promotion and Prevention Strategies for Group 1

Table 3.11 presents the parameter estimates of the migration mechanisms across four paths for Group 2 (repeat customers with higher engagement and more complaints but less expression of compliments). Overall, these customers seem to benefit from two dimensions of CX, affective and cognitive, for both promotion and prevention purposes.

Specifically, affective CX not only increases the probability of shifting up but also reduces the likelihood of moving down. For Group 2 members in N states, the higher the number of affective CXs, the higher the probability of transferring to P-P state (0.15, significant at 1%). Moreover, for the same group in states P-P and P-A, the higher the level of affective elements in their experiences, the lower their likelihood of descending to N state (-0.06 and -0.14, both are significant at 1%). Similarly, the higher the cognitive CXs, the greater the probability of transferring from N state to P-A state (0.02, significant at 5%).

For the same group in states P-P and P-A, the higher the level of the cognitive dimension within their experiences, the lower the likelihood that consumers will decline from P-A or P-P states to N state (-0.02 and -0.01, both are significant at 5%). In addition, the higher the level of social and physical CXs, the lower the probability of transferring from P-A state to N state P-P (-0.02, and -0.04, both are significant at 5%). For repeat customers in Group 2 in P-P state, the higher the level of physical-sensory components in their experiences, the less likely they are to decline to N state (-0.05, significant at 1%). Interestingly, social CX also backfires for Group 2. Our results show that for people in N state, the higher the number of social CXs, the lower the probability that they will transition to P-P state (-0.11, significant at 1%). Similarly, the higher the number of social CXs, the greater the likelihood of declining from P-P state to N state (0.04, significant at 1%).

Table 3.11 Transition Probability Parameters: The Long-Term Effects of Migration Mechanisms on CET for Group 2

Group 2: Less Compliments with Higher Engagement	**Increasing the Probability of Moving Upward from N State to P-A/P-P States (Positive Coefficients Expected)**		**Decreasing the Probability of Moving Downward from P-A/P-P States to N State (Negative Coefficients Expected)**	
Mechanism 1	**From N to P-A State**	**From N to P-P State**	**From P-A to N State**	**From P-P to N State**
Affective CX	0.03 (0.03)	**0.15***** **(0.03)**	**-0.06***** **(0.02)**	**-0.14***** **(0.01)**
Cognitive CX	**0.02**** **(0.01)**	0.01 (0.01)	**-0.02**** **(0.01)**	**-0.01*** **(0.01)**
Social CX	-0.02 (0.02)	**-0.11***** **(0.02)**	**-0.02**** **(0.01)**	**0.04***** **(0.01)**
Physical CX	-0.02 (0.04)	0.01 (0.04)	**-0.04**** **(0.02)**	**-0.05***** **(0.02)**
Mechanism 2	From N to P-A State	From N to P-P State	From P-A to N State	From P-P to N State
Accuracy	-0.08 (0.13)	-0.12 (0.14)	0.08 (0.06)	-0.1 (0.11)
Communication	-0.03 (0.05)	0.04 (0.04)	-0.05 (0.04)	-0.05 (0.03)
Cleanliness	0.12 (0.12)	0.13 (0.13)	**-0.14**** **(0.07)**	**-0.11**** **(0.06)**
Location	0.08 (0.06)	0.06 (0.06)	-0.04 (0.03)	**-0.06***** **(0.02)**
Check-In	-0.04 (0.16)	0.04 (0.21)	0.02 (0.08)	0.06 (0.05)
Value	-0.01 (0.08)	-0.05 (0.09)	0.02 (0.05)	0.03 (0.03)

Note: ** significant at 5%; *** significant at 1%

Turning to the long-term effects of the six experience evaluating criteria that service providers can control, we find that, for Group 2 customers, these six perceived managerial actions are not significant for promotion propose. However, they can be seen as prevention strategies that may be used to decrease the likelihood of downward migrations for the repeat customers in Group 2. The two prevention mechanisms include cleanliness, which reduces the likelihood of moving down from state P-A to N and from state P-P to N (-0.14 and -0.11, respectively, both significant at 5%) and convenience of location, which decreases the deterioration probability from P-P to N state (-0.06, significant at 1%).

Generally, for repeat customers in Group 2 whose most likely potential destination is P-A state, both mechanism 1 and mechanism 2 are more effective as prevention strategies to decrease the downward probabilities than as promotion strategies to increase the upward likelihoods. Interestingly, social CX also exerts backfire effects on this group. That is, increasing Group 2's perceptions of the social dimension of CX will not only undermine their upward migration from N to P-P state, but also aggravate the downward probabilities from P-P to N state.

Figure 3.7 depicts the directions that can be used to identify how to deploy the relevant migration strategies, given the CET states for the second segment (Group 2) of repeat customers. Drawing on our empirical results from **Table 3.11**, the promotion strategies describe the most efficient tactics to trigger positive state change (from N to P-P/P-A states); the preventive strategies indicate the most efficient tools for preventing negative state change (from P-P/P-A states to N state).

The Effectiveness of Migration Mechanisms on Group 2 (Size=45.52 %) : Less Compliments with Higher Engagement

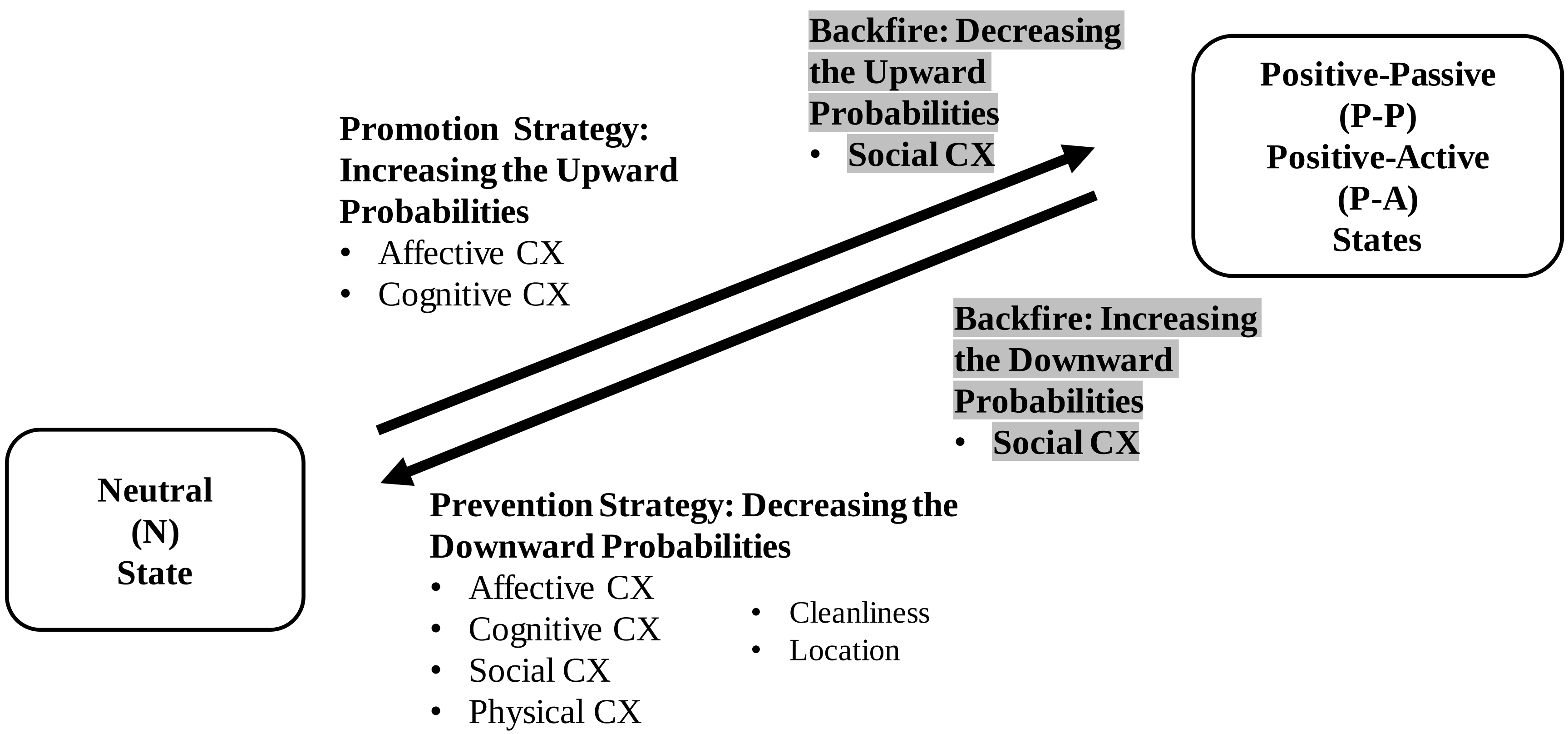


Figure 3.7 The Effective Promotion and Prevention Strategies for Group 2

3.4.2.6 The Marginal Effects of Migration Mechanisms

To quantify the marginal effects of the effective migration mechanisms identified in **Tables 3.10** and **3.11**, we calculate the transition probabilities when the mean value of a variable increases by one standard deviation for cleanliness, location, and affective CX while holding the other variables constant. Matrices (b), (c), and (d) in **Table 3.12** report the transition probabilities caused by such a change in the focal variable. We focus on cleanliness and location because they are verified as being effective in decreasing the likelihood of moving downward for both groups. Moreover, experience providers can readily manage these variables. For example, if the experience provider offers a pick-up service at the airport, or instructions for how to use public transportation to visit attractions, or information about places to eat that are well-known to locals but not to tourists, then the mean value of the convenience of location is likely to increase. We can then use the difference between the respective cells of (a) and (b)-(d) to calculate the marginal effect on the transition probability. For example, in matrix (b), a one-standard-deviation increase in cleanliness in Group 2's repeat experience will increase the probability of transitioning from N state to P-P state by 13% (from 21% to 34%) and increase the probability of remaining in P-P state by 11% (from 18% to 29%). Moreover, it will decrease the likelihood of downward migration for Group 2 from P-P state to N state by 23% (from 27% to 4%) and reduce the likelihood of deteriorating from P-A state to N state by 29%. Similarly, in matrix (c), increasing the convenience of location by one standard deviation could increase the probabilities of Groups 1 and 2 transitioning to desirable states (P-P/P-A states). Additionally, the marginal effect of location can decrease the probability of moving down to undesirable state N for both groups. Finally, as we show in matrix (d), the most effective variable for the experience providers' promotion and preventive strategies is affective CX, which has higher marginal returns in terms of shifting customers to P-P state and preventing them from drifting to N state.

Table 3.12 Marginal Effects of Cleanliness, Location and Affective CX

(a) The Original Transitional Matrix **(Baseline)**

Group	From	To: P-P	To: P-A	To: N
1	P-P	0.83	0.12	0.05
1	P-A	0.54	0.36	0.10
1	N	0.67	0.13	0.20
2	P-P	0.18	0.55	0.27
2	P-A	0.15	0.53	0.32
2	N	0.21	0.45	0.34

(b) The Marginal Effects of Increasing Cleanliness

Group	From	To: P-P	To: P-A	To: N
1	P-P	0.91	0.07	0.02
1	P-A	0.52	0.36	0.13
1	N	0.54	0.05	0.41
2	P-P	**0.29**	**0.66**	**0.04**
2	P-A	**0.21**	**0.77**	**0.03**
2	N	**0.34**	**0.62**	**0.04**

(c) The Marginal Effects of Increasing Convenience of Location

Group	From	To: P-P	To: P-A	To: N
1	P-P	**0.90**	0.07	**0.03**
1	P-A	**0.74**	0.21	**0.05**
1	N	**0.79**	0.06	**0.15**
2	P-P	**0.28**	**0.62**	**0.10**
2	P-A	**0.25**	**0.61**	**0.14**
2	N	**0.22**	**0.70**	**0.08**

(d) The Marginal Effects of Increasing the Affective CX

Group	From	To: P-P	To: P-A	To: N
1	P-P	**0.91**	0.06	**0.03**
1	P-A	**0.77**	0.19	**0.04**
1	N	**0.87**	0.07	**0.06**
2	P-P	**0.33**	**0.58**	**0.08**
2	P-A	**0.35**	**0.57**	**0.08**
2	N	**0.48**	0.38	**0.14**

3.5 Discussion and Contribution

This study presents an integrative nonhomogeneous HMM model that accounts for cross-individual heterogeneity to dynamically target repeat customers and strategically allocate managerial resources. The HMM model accounts for unobserved heterogeneity across consumers and captures the dynamics within consumer behaviors, the evolution of CET, and the short- and long-term effects of the migration mechanisms on the CET. The application of our modeling framework in the context of repeat customers' Airbnb experiences reveals several insights. First, we identify two segments of repeat customers: a group that is more complimentary with lower engagement (Group 1) and a group that is less complimentary with higher engagement (Group 2). Empirical results show that there is more managerial space for marketers to influence Group 2. Second, we determine three CX performance states for repeat customers: the neutral (N) state; the positive-active (P-A) state; and the positive-passive (P-P) state. These range from a lower to a higher level though an increase in the summative score for revisit, referral, and compliment behavior, and a decreasing trend in complaints. The most likely potential destination for Group 1 is P-P state and the most likely potential destination for Group 2 is P-A state. Third, we investigate the short-term effect of two migration mechanisms (the four dimensions of CX and six management-related actions perceived by repeat customers) on transitioning repeat customers between the three CX performance states. We find that the affective-emotional dimension of CX is positively associated with being in the higher level states (P-A/P-P states) but negatively associated with being in the lower N state. In contrast, the social-relational dimension of CX negatively influences the likelihood of being in the higher CX performance state but positively influences the likelihood of being in a lower one. These short-term effects echo our findings about the long-term effects exerted by the affective and social dimensions of CXs. That is, affective CX will positively determine the formation of the higher CX performance state (P-P) in the short run and increase the upward likelihood in the long run. In contrast, social CX will determine the formation of the lower CX performance state (N) in the short run and will backfire on the desirable transition paths in the long run. Regarding the management-related variables, communication, cleanliness, and the convenience of location exert a positive, short-term effect on being in the higher level states (P-A/P-P) but a negative effect on being in the lower performance state (N). Fourth, regarding the long-term effects of the migration mechanisms, both cleanliness and location have long-term impacts as a safeguard against moving downward. Fifth, social-relational CX "backfires" by exerting contrary long-term effects on the desired transitional directions. Sixth, affective CX is the most effective variable, acting as a promotion and prevention tool in both the short- and long-term.

3.5.1 Theoretical Contributions

The aim of this paper is to advance the theories on dynamic CX and CXM in several ways. We disentangle the joint dynamics between CX and CB. This is the first study to test the inherently dynamic nature of the CET in the CX literature using repeat customers' longitudinal verbatim data (six separate comments from a single customer concerning the same accommodation listed on Airbnb), and leveraging natural language processing techniques to capture the dynamic development of experience by building a Hidden Markov model. This dynamic perspective is a unique feature since the existing CXM literature relies on a conventional approach that implicitly assumes that the relationships among the desired CBs (performance), influential mechanisms, and CX are static in nature (Barkus et al., 2009; Bleier, Harmeling, & Palmatier, 2019; Barkus et al., 2009; Iglesias, Singh, & Batista-Foguet, 2011; Lee, Lee & Kang, 2012; Schmitt et al., 2015).

Specifically, our dynamic model allows the effect of migration mechanisms to change across customers and over time. As such, our approach not only advances the CX and CXM literature but also expands an aspect of RM that largely contradicts managers' intuition: repeat customers are not always in a static sate, and not every repeat customer's relationship strengthens or evolves monotonically over time. There are different evolutionary patterns among the repeat customers and experience providers, and managers can tailor their activities to accommodate these differences. Our empirical analysis indicates that the positive-passive (P-P) state gains the largest number of customers over time, followed by the positive-active (P-A) state. These two CX performance states are favorable for the experience providers, as they exhibit a higher level of referral, revisit intention, and positive WOM (compliments) and a lesser amount of negative WOM (complaints). Specifically, once the repeat customers are in Group 1 (the more complimentary with lower engagement group), they tend to migrate to the positive-passive (P-P) state. For the repeat customers in Group 2 (the less complimentary with higher engagement group), their most likely destination is the positive-active (P-A) state. Regarding the neutral (N) state, this trajectory exhibits the lowest level of desirable behaviors (positive WOM) and the highest level of negative WOM.

To the best of our knowledge, this is the first study to examine how the different dimensions of the CX and managerial actions influence transitions across the CET. In addition, our results from the dynamic model provide insights for the Airbnb platform and Airbnb hosts since we utilize the six experience evaluation criteria from the Airbnb website as the management-related variables to test their short- and long-term effectiveness. We find that the results of these effects on state-dependent distributions help to determine the formation of CX performance states in the current period, such that communication, cleanliness, and convenience of location are positively related to the higher performance state (P-P) in the short run. However, the managerial related variables have no obvious long-term effect on the evolution of repeat customers' CETs, except for the impacts of cleanliness and convenience of location on preventing downward movement (through changing transitional probabilities) by Group 2 in the long run.

More interestingly, the empirical results reveal that social CX backfires, not only in terms of decreasing the likelihood of customers moving to a higher CX performance state but also by increasing the probability of them migrating to a lower state. When we examine this backfire effect exerted by social CX, we find that two critical social components (friends and family) have significantly negative associations with compliments, referrals, and revisit intentions in our dataset. We note that when repeat customers mention their friends or families in their online reviews, the comments tend to be negatively associated with the expressions of favorable words. Therefore, we argue that the focal repeat customers will go online to voice their friends' and families' unsatisfactory/bad experiences but not their positive ones. Consider the following situation: there is a repeat customer on Airbnb whose family/friends are staying with him at Alice's place, which is where he always stays when visiting New York City. However, he later discovers that his family/friends did not enjoy their stay at Alice's house. We postulate that this situation operates as an identity threat for the focal repeat customer. The psychology literature provides ample evidence that identity threats will motivate consumers to bolster their self-concept (Dunning, Perie, & Story, 1991; Escalas & Bettman, 2005; Hennig-Thurau et al., 2004; Sundaram, Mitra, & Webster, 1998; Wentura & Greve, 2005). We argue that, in this situation, the customer may be motivated to bolster his threatened identity, and one way of doing this would be to act as an online agent for his family/friends and provide a voice for them. This might lead to the negative relationships between social CX and referral, revisit, and compliments as well as explaining the backfire effects exerted by social CX on repeat customers' CETs.

Finally, our results indicate that the affective-emotional dimension of CX is the most effective tool for two purposes (the promotion and prevention strategies) in the long-term but is also effective in the short-term as a means of prompting customers to move to a higher CET state. These results highlight the usefulness of employing affective-emotional components as a migration mechanism, especially in switching repeat customers to a higher CET state and retaining them there.

Overall, this research makes the following theoretical contributions. First, we contribute to the CX literature by providing insights into the evolution of repeat customers' experience trajectory. Second, we contribute to the CX literature by being the first to uncover the co-evolution phenomenon between CB dynamics and CX dynamics through the use of a single dynamic model. Our third contribution to the CX literature is our finding that management resources might be more effective when targeted at Group 2 rather than Group 1. In our research, we account for the dynamics by modeling the transitions among different segments. Moreover, we examine both the short- and long-term effects of the two sets of migration mechanisms. Our estimates of customer responses to management activities have a degree of precision that will enable managers to be better informed when they are making resource allocation decisions. Finally, this article provides a methodological contribution to the research stream regarding text mining and online reviews, as we are the first study to leverage customers' longitudinal textual reviews as the basis for building an HMM.

3.5.2 Managerial Takeaways and Future Research

Our results provide important managerial implications for devising various mechanisms and evaluating their effectiveness. In **Figures 3.6** and **3.7**, we parsimoniously demonstrate that managers can deploy relevant CXM migration strategies, given the identified CX performance states (N, P-A, P-P states) and repeat customer segmentations. We provide dynamic experience migration strategies for each CX performance state that can make actionable recommendations for managers who have identified their customers' states and segments. For example, for both groups, managers need to avoid the backfire effects that ensue from the social-relational dimension of CX by dedicating specific attention to repeat customers who bring their family or friends or colleagues or partners to the service experience. If there is negligent action that the repeat customers' friends/family might perceive as unfair or unsatisfactory, then managers need to react quickly before the social components of CX exert a backfire effect. More importantly, managers need to pay more attention to both groups by actively improving their experience through increasing the affective-emotional components of service interactions; for example, consumers will take the employees' (staff's) emotional displays as key indicators of the service provider's intentions and sincerity. We suggest that it is the congruence of the inner emotions and external behavioral displays that result in repeat patronage and long-term relationships with customers. Affective environmental components, such as pleasant music, a fresh scent, bright lights, and soft fabrics, will also evoke pleasure and arousal, which leads to the desire to stay longer and recommend the experience to others.

As regards the direction of future research, it will be useful to extend the current research results from the individual customers' perspectives to the firms' perspectives. Future research could focus on firms' CX performance and the dynamics of firms' CX performance states, shedding light on how to design effective customer experience management strategies throughout the firm's trajectory of its CX performance.

This study suffers from certain limitations that must be acknowledged although some of these limitations can be seen as avenues for future research. First, only repeat customers' longitudinal comments (six periods of panel data) were leveraged to identify the switching patterns. It would be worth integrating the same focal customers' transaction data, their online portfolio (e.g., tenure, personal information, characteristics), and the service provider's observable data (e.g., their aggregated rating score, their responses to guests) to construct the CX performance states. We suggest that other state variables might capture additional facets and result in more nuanced CX performance states. Second, we suggest that the generalizability and robustness of this analysis could be enhanced by employing a broader sample of non-repeat customers, switching the perspective from the individual level to the firm level, or expanding the research context from the service industry to other sectors. We recommend that future research might dynamically expand the analysis to examine firm-level dynamics. Our collection of longitudinal comments about the same service providers is a significant undertaking that enabled us to study the individual-level experience dynamics. However, the trajectories we have presented relate to six occasions per customer and so might not present the full spectrum of the focal customers' experience trajectory. Further research, based on more comprehensive and firm-level data across more industries, might make it possible to model the experience trajectories from initiation to dissolution, thereby increasing generalizability and painting a more detailed picture of our proposed CET framework.

Chapter 4: Study 2

Dynamically Managing the Firm's Customer Experience Performance Trajectory: A Value Co-Creation Perspective

Abstract

Customer experience management (CXM) is among the marketing approaches that offer the most promise for increasing profits in consumer industries. However, the extant research is insufficient to properly understand the effectiveness of changes to CXM strategies over time. According to our research framework, the trajectory of a firm's customer experience (CX) performance, through which experience providers migrate through different performance states over time, suggests that not all CXM strategies are equally effective. Thus, given the CX performance states of a firm, it is possible to identify the best combination of effective strategies. We suggest a dynamic framework that integrates prior research on CX, dynamic relationships, and value co-creation to better understand and manage firm CX performance. We offer CX insights that are gained from longitudinal textual data through text mining and dictionary development techniques. We apply a hidden Markov model to identify four latent CX performance states and parsimoniously capture the migrations of firms' CX performance through double-faceted value co-creation mechanisms, incorporating their positive and negative aspects. We disentangle the dynamic effectiveness of migration strategies across different performance states, the results of which can help firms propel their performance into the

higher states or prevent deterioration to the lower states. The results enrich the extant CX and value co-creation theories while improving CX managers' practices and providing managers with guidelines for their allocations of dynamic CXM resources.

4.1 Introduction

With the popularity of experiential purchases on the rise, understanding and creating a strong customer experience (CX) is now an important management objective (Lemon & Verhoef, 2016). The customer experience management (CXM) market is projected to grow from USD 7.8 billion in 2019 to USD 14.5 billion by 2024, forecasting a compound annual growth rate of 13.3%. Practitioners have begun to regard CXM as one of the most promising management approaches for meeting market challenges (Homburg et al., 2017). In academia, a substantial body of work in the CX research domain has furthered our understanding of the nature of CX by proposing and testing the CX construct and its related frameworks (e.g., Barkus, Schmitt, & Zarantonello, 2009; Grewal, Levy, & Kumar ,2009; McColl-Kennedy et al., 2019; Ordenes et al., 2014; Puccinelli et al., 2009; Tax et al., 2013; Verhoef et al., 2009). CX scholars and practitioners now agree that CX is a holistic, multidimensional construct that centers on a customer's cognitive, emotional, behavioral, social, and sensorial response to a firm's offering during the customer's experiential journey across multiple touchpoints (Lemon & Verhoef, 2016). Although previous theoretical work has conceptualized the overall CX as a dynamic process or journey, much of the empirical CX literature still treats it as temporally homogeneous, implying that customers respond in similar ways to firms' initiatives. Thus, extant literature ignores the dynamic nature of the CX journey, leading to a lack of accuracy in the design of management actions to control CX and a lack of appropriateness in the dynamic deployment of management resources. Moreover, most research focuses on the CX or consumer journey from the perspective of an individual customer (e.g., Brakus et al., 2009; Grewal et al., 2009; Novak et al., 2000, Schouten et al., 2007; Verhoef et al., 2009). That is, current scholarship has largely failed to examine this indubitably dynamic phenomenon through a collective lens. We argue that there is no research that tackles a firm's CX performance trajectories as they are collectively perceived and evaluated by its customers, leading to a gap in our understanding of dynamic CX management. Thus, in this contribution to the CX literature, we address that knowledge gap and explore how different CX management strategies vary in terms of their effectiveness throughout the CX performance trajectories from the firms' perspectives.

To unpack the dynamic nature of CX trajectories, we leverage some recent research into other realms that use dynamic modeling approaches (e.g., the Hidden Markov Model) and suggest the importance of acknowledging latent states as a means of understanding the dynamic phenomena. For example, specific marketing actions might be more effective when customers are in certain states than when they are in others (Luo & Kumar, 2013; Netzer, Lattin, & Srinivasan, 2008). Previous researchers have leveraged the flexibility of dynamic models to uncover customers'/firms' migration patterns across latent states and identify their distinct responses to state migrations (e.g., Fader & Hardei, 2010; Homburg, Steiner, & Tozek, 2009; Netzer et al., 2008; Rust and Verhoef 2005; Zhang et al., 2016). We contend that this concept of capturing dynamics from datasets is useful in our research setting, in that CXs are dynamic in nature and certain CX management strategies might be more effective than others. However, most of the existing literature utilizes a dynamic perspective to model a time series of observations in B2B, B2C, or C2C contexts at the individual or firm level, capturing their behavioral relationship dynamics at the same, corresponding level (e.g., Ascarza, Netzer, & Hardie, 2018; Netzer et al., 2008; Zhang, Netzer, & Ansari, 2014). This means that the majority of dynamic studies use a single level of data measurement to conduct data analysis, and use a same-level lens to provide a snapshot of dynamic phenomena. Moreover, as discussed in the above paragraph, most of the current CX literature specifically focuses on the individual level perspective. Therefore, to extend the research focus into the firm's level and form a complete picture of CX performance trajectories, we seek to leverage recent efforts from other fields (e.g., origination behavior) regarding an aggregate concept, whereby lower-level entities are aggregated into higher-level constructs (Cohen, 2007). For instance, Salvato (2009) used longitudinal, individual level data to provide a new understanding of the individual's role in a firm's capability evolution. Salvato's work examined the connection between the daily activities of individuals and the evolution of the firm's new product development capability. Some psychological research further extends our knowledge of how micro factors, such as individual emotions and interactions, may affect firm-level outcomes (Hertwig & Ortmann, 2001; Intille, 2006). In this study, we aim to bridge the different levels by aggregating lower level data related to an individual's CX perception to measure higher level constructs concerned with a firm's CX performance. We contribute to the literature by providing a different understanding of dynamic phenomena using cross-level lenses. Our goal is to use longitudinal individual-level data points to test dynamic phenomena at the firm level.

Moreover, extant CX theory offers little insight into the strategies that managers can use to influence customers' migration across different experience states. Nor does it explain which of the different migration strategies ultimately affect customers' perceptions of firms' CX performances. In this sense, we seek to advance CX management theory. By leveraging the value co-creation theory and the corresponding value creation elements that have been advanced by previous contributors (McColl-Kennedy et al., 2019; McColl-Kennedy et al., 2012; Macdonald, Kleinaltenkamp, and Wilson 2016; Ordenes et al., 2014), we develop a holistic CX management mechanism that parsimoniously captures/influences the migrations in the latent states of a firm's CX performance. Adapting the work of Macdonald et al., 2016, McColl-Kennedy et al., 2012, McColl-Kennedy et al., 2019, and Ordenes et al., 2014, we propose the ARCI value co-creation mechanism, comprised of four value co-creation elements: activities (A), resources (R), contexts (C), and interactions (I). Moreover, we tailor the ARCI value co-creation elements by developing a positive mechanism for upward migration and a negative mechanism for downward migration among the levels. Each migration mechanism reflects the unique patterns of a firm's latent states and captures the development or decline in the trajectory of the firm's CX performance. We test the distinct effectiveness of the proposed positive and negative migration mechanisms, which are composed of the ARCI components, to infer the managerial impacts on firms' CX performance dynamics. Our research contributes to the literature by adopting the value co-creation perspective from the service literature and using it in the CX management realm. We integrate the concepts of CX dynamics and value co-creation as the appropriate theoretical underpinnings for tackling the major question of how to dynamically manage firms' CX performances.

Finally, to measure CX dynamics and CXM mechanisms, previous researchers have suggested that linguistics-based and natural language processing techniques might offer an opportunity to gain essential insights from the big data that is created throughout the consumption journey (e.g., Keiningham et al., 2017; Lemon & Verhoef, 2016; McColl-

Kennedy et al., 2019; Ordens et al., 2014; Verhoef, Kooge, & Walk, 2016). However, Ordenes et al. (2014) argue that the complex holistic nature of CX makes it challenging to measure customer perceptions of interactive service experiences. Thus, the advances and challenges related to increasing volumes of unstructured textual data make it difficult for managers to analyze and interpret this information. Aside from the study of Berger et al. (2020), there is little research to guide CX scholars and practitioners in how they might exploit consumers' verbatim comments to generate insights into CX dynamics and predict the dynamic effects of CX strategies. We address this by leveraging the text analysis workflow provided by Berger et al. (2020), with the aim of deriving rich insights from textual data. We integrate several linguistic-based approaches, convert the text into quantifiable measures, assess the validity of the extracted measure, and generate final numeric metrics to analyze our proposed research framework. In this research, we use a web crawling technique (programmed in Python) to collect customers' online reviews and individual rating scores on the Booking.com website. We focus on 1,054 hotels in New York City on Booking.com, gathering the 300 most recent comments received by the focal hotels during the timeframe of June 1 2019 to August 30 2019, resulting in a total of 131,566 guest comments and rating scores given by the guests. We choose New York City (NYC) because it is the largest city in the U.S, and June to August because this is the peak season for the NYC hotel industry. This provides us with the opportunity of collecting a large number of reviews that reveal the different aspects, needs, perceptions, and evaluations of a miscellany of customers (e.g., business travelers, families, backpackers), offering hotels with greater opportunities for understanding the multiplicities of their clients. Moreover, our rationale for collecting customers' reviews from Booking.com is that this website allows guests to directly leave comments about their hotel stay experiences that are both positive (compliments) and negative (complaints). This enables us to measure the positive and negative facets of our focal concept, the ARCI value co-creation mechanism.

Rather than developing an individual-level empirical model from the individual customer's perspective, this study models aggregated data to be used as a proxy to understand CX performance at the firm's level. That is, our research takes the firm's perspective; although we collect induvial clients' datapoints, the customer data are analyzed and managed through the lens of the firm's managers (i.e., at the collective level). The aim of this research is to answer the following questions: (1) How does the trajectory of firms' CX performance evolve over time? (2) How many latent states of CX performance can be identified in the dataset? (3) How do the ARCI migration mechanisms, comprising Activities, Resources, Contexts, and Interactions, influence the transition across different CX performance states? That is, given a firm's current state, what is the most effective strategy/element for migrating it to a higher performance state or for preventing it from sinking to a lower performance state? The remainder of this article is organized as follows. We present the research framework by reviewing the current literature on CX, customer dynamics, HMM, and value co-creation theories. Then we develop the HMM for examining the proposed research framework. After describing the dataset and the methodology used in this paper, we report the results. The paper concludes with a discussion of its academic contributions and managerial implications.

4.2 Theoretical Background and Research Framework Development

4.2.1 Understanding the Multidimensional Nature of CX and CX Performance

CX is a central focus of marketing theory and practice (McColl-Kennedy, 2019). Schmitt, Brakus, and Zarantonello (2015) suggest that every service exchange, regardless of its nature and form, leads to CX. Meyer and Schwager (2007) broadly define CX as the internal and subjective response of a customer to any direct or indirect contact with a company. Gahler, Klein, and Paul (2019) characterize CX from the customer's perspective as subjective and holistic (the latter being a concept they trace back to Gestalt psychology, which builds on the principle of totality) (Koehler, 1938; Koffka ,1935; Wertheimer, 1945). According to this school of thought, the components of the human mind are all inter-linked. Thus, individuals perceive experiences holistically by simultaneously considering all of the internal and behavioral components. Consistent with the holistic principle, Pinker (1997) posits a psychological concept concerned with the modularity of the mind (Pinker, 1997) to distinguish three basic systems of sensation, cognition, and affect. This, in turn, supports the multidimensionality of CX.

Schmitt (1999) also proposes a modular conceptualization and identifies five types of experience: sensory (sense); affective (feel); cognitive (think); physical (act); and social-identity (relate). Gentile, Spiller, and Noci (2007) hold that the CX can be defined as a set of interactions that provokes reactions between a customer and provider; they imply the customer's involvement at different levels (rational, emotional, sensorial, physical, and spiritual). Verhoef et al. (2009) define CX as holistic in nature, involving the customer's cognitive, affective, emotional, social, and physical responses to the retailer. Brakus, Schmitt, and Zarantonello (2009) define brand experience as consisting of four separate, albeit related, dimensions: sensory; affective; intellectual; and behavioral. De Keyser et al. (2015) describe the consumer experience as comprising cognitive, emotional, physical, sensorial, spiritual, and social elements that mark the customer's direct and indirect interaction with other market actors. Schmitt, Brakus, and Zarantonello (2015) consider CX to be holistic in nature, incorporating the customer's cognitive, emotional, sensory, social, and spiritual responses to all interactions with a firm. Other research argues that the physical factors of CX include multi-sensations, ambiance, physical features, and artifacts (Walls et al., 2011). Several researchers have studied the cognition factors in terms of the disconfirmation paradigm, which predicts satisfaction to be a function of the comparison between expectation and performance (e.g., Bearden & Teel, 1983; LaBarbera & Mazursky, 1983; Oliver, 1980; Oliver & DeSarbo, 1988). Following an intensive review of the literature on CX, we argue that all of these dimensions of CX can be classified under four major categories. We submit that the CX construct is holistic and multidimensional in nature, involving the customer's (1) cognitive-rational, (2) affective-emotional, (3) social-relational, and (4) physical-sensory responses to the product/service providers, in line with the four primary systems commonly studied in the fields of psychology and sociology (Anderson, 1985; Pinker, 1997). More details of this can be found in the literature review section in study 1.

We propose that the next stage of research is to move the focus away from the individual level of a discrete consumer to develop a broader understanding of CX performance from the service provider's perspective. We argue that firms' CX performance can be expressed by individual customers' CX perceptions and evaluation. Rousseau (1985) asserted, in relation to multi-level theoretical frameworks, that in order to avoid fallacies of the wrong level, scholars must simultaneously consider the theory, measurement, and analysis for the levels of the constructs included in their investigations, and that these three facets must be aligned to minimize level-related confounds. We submit that, through data aggregation, the aggregated individuals' evaluation/perception of their experience toward the experience provider/firm may serve as a proxy for the focal provider's CX performance. We further extend the nature of the CX concept (Lemon & Verhoef, 2016) to incorporate the firm's CX performance. In line with the individual customer's CX experience, we argue that the firm's CX performance is also holistic and multidimensional, expressed by the perceptions and evaluations of the receivers and consumers of the experience, and it includes the cognitive, affective, social, and physical responses of the experience provider. Applying this definition to our research context, we argue that the perceived CX performance is created not only by the elements that the experience providers can control (e.g., service quality, price, frontline employees' interactions) but also by elements that lie outside the experience providers' control (in our context, these include consumers' motivations and expectations, influences of others, traffic, and the external surroundings of the hotel). The next sections will focus on a richer conceptualization of firms' CX performance to capture its inherently dynamic nature and the drivers that influence firms' CX performance.

4.2.2 Understanding the Dynamic Nature of CX and CX Performance

Several researchers suggest that the dynamic effects of CX can occur within customers as the customers themselves change over time following repeated experiences with a product (Lemon & Verhoef, 2016). To develop a theoretical foundation for the CX performance trajectory, we borrow concepts from the customer dynamics and relationship management (RM) realms. RM scholars agree that relationships evolve over time and are fundamentally dynamic in nature (Harmeling et al., 2015; Kozlenkova et al., 2017; Palmatier et al., 2013; Zhang et al., 2016). Many empirical RM studies use the term "stage" to identify empirical differences and thereby capture the development that encompasses the growth, maturation, and decay of relationships over time (Heide, 1994; Hibbard et al., 2001; Jap & Anderson, 2007; Jap & Ganesan, 2000). As Grayson and Ambler (1999) note, the length of a relationship changes the nature of the relational constructs, and the exact nature of these relational dynamics remains elusive.

In addition to the evolution/change of relationship stages, other researchers have investigated customer dynamics as they relate to choice modeling (Netzer, Lattin, & Srinivasan, 2008; Montoya, Netzer, & Jedidi, 2010), behavioral change (Rust & Verhoef, 2005), retention rates (Fader & Hardie, 2010), churn rate (Azcarza et al., 2018), and customer portfolio management (Homburg, Steiner, & Totzek, 2009). Loyalty researchers also agree that consumers' loyalty behaviors and attitudes evolve over time (e.g., Dick & Basu, 1994; Johnson, Herrmann, & Huber, 2006; Jones & Sasser, 1995; Ngobo, 2017; Oliver, 1999). Satisfaction researchers propose several crucial notions that have paid attention to the dynamic development of customer satisfaction (e.g., Bolton & Drew, 1991; Boulding et al., 1993; Mittal et al., 1999), suggesting that current customer satisfaction affects future expectations. These researchers move the existing relationship marketing models into the sphere of customer dynamics by incorporating conversion and switching probabilities.

Moreover, the abovementioned empirical research has noted the flexibility of the dynamic modeling approaches (e.g., Hidden Markov Model, HMM). Much of the research on dynamic topics has used a dynamic modeling approach to identify latent states based on observed customer behavior (Luo & Kumar, 2013; Netzer, Lattin, & Srinivasn, 2008; Zhang et al., 2016). These dynamic models are useful for studying behavioral patterns because they describe the latent relationship through discrete states at any given point in time, uncovering the migration patterns across states and identifying the variables responsible for state migrations (Zhang et al., 2016). In essence, the dynamic model is well suited for inferring latent states from observed behaviors such that individuals/firms can flexibly migrate between different states (Luo & Kumar, 2013; Montoya, Netzer, & Jedidi, 2010; Zhang, Netzer, & Ansari, 2014). For example, Zhang, Waltson, Palmatier, and Dant (2016) identify buyer-seller relationship states and capture customers' migration across relationship states via three positive and two negative migration mechanisms. Ngobo (2017) uncovers three latent states to depict the trajectory of customer loyalty and the effectiveness of certain marketing actions in influencing customers' transitions across loyalty states, such as a private label policy, feature advertising, product display, and store pricing policy. Chen, Wei, and Zhu (2018) use latent motivational states to characterize the dynamics of user contributions in online communities and focus on three mechanisms (reciprocity, peer recognition, and self-image) for transitioning users between the latent states.

However, given the relative immaturity of the CX literature, there is limited empirical work directly related to the dynamic nature of firms' trajectories of CX performance. Thus, we extend the customer dynamic concept and argue that it is necessary to develop a research framework and employ a rigorous approach to capture the evolution of the trajectory of a firm's CX performance. The present study leverages the metrics of a dynamic model (i.e., HMM) to study the dynamics of firms' CX performance. Through the flexibility of HMM, we not only empirically identify the firms' CX performance states from our dataset, but also employ the dynamic model's parsimonious property to reveal the degree of transience or stickiness of the different CX performance states. These properties of dynamic modeling are well suited to our research objective, which is to disentangle the dynamics of our sampled firms' CX performance.

4.2.3 Understanding and Managing CX Performance Using Value Co-Creation Perspective

Service researchers propose that the customer should be regarded as an active rather than passive recipient of services (Baron & Harris, 2008; Payne, Storbacka, & Frow, 2008; Xie, Bagozzi, & Troye, 2008). They acknowledge that consumers' value co-creation might extend beyond the boundaries of the firm and that value is not realized until the service is consumed; that is, it is value-in-use (Cova & Salle, 2008; Grönroos & Voima, 2013; Payne, Storbacka, & Frow, 2008; McColl-Kennedy et al., 2012; Prahalad & Ramaswamy 2000; 2003; 2004). Vargo and Lusch (2004; 2008) propose the service-dominant (S-D) logic, where value co-creation is regarded as being accomplished through resource integration. Following S-D logic, Heinonen et al. (2010) and McColl-Kennedy et al. (2012) report that co-creation value is realized through the activities and interactions with collaborators in the customer's service network, and that this is embedded in the customer's contexts. Ordenes et al. (2014) propose an empirical ARC framework comprising three essential elements of CX: activities, resources, and context. In line with Ordenes et al. (2014), McColl-Kennedy et al. (2019) view CX as consisting of the following five value creation elements: activities; resources; context; interaction; and customer roles. As highlighted by other service researchers (Baxendale, McDonald, & Wilson, 2015; Gentile, Spiller, & Noci, 2007), CX originates from a set of interactions, such that the customer's evaluations of the service experience are an outcome of these interactions.

Adapting the conceptualizations mentioned above, we apply the perspective of value co-creation into our research settings. We argue that CX is co-created by two parties: the experience providers and the experience receivers, and that value is derived from a co-creation process of CXs. We note that the co-creation of value from CXs consists of at least two aspects, with customers on one side and firms on the other. The perspectives of both sides regarding how best to create value together must be addressed (Gupta, Lehmann, & Stuart, 2004). Following this reasoning, we argue that firms' CX performance is also co-created by experience providers and experience receivers, and that this is further perceived and evaluated by the experience receivers. Moreover, there is value co-created within the experience encounters, which is realized by the integration of resources through activities and interactions between experience providers and receivers in the CX contexts; this is a process that emphasizes the roles of activities, resources, interactions, and contexts between experience providers and recipients during the CX encounters (Shostack, 1985). These CX encounters are critical for customers' CX perceptions in terms of the firms' CX performances, leading to the results of satisfaction (Bitner et al., 1994; De Ruyter et al., 1997), service quality (Parasuraman et al., 1994), and customer loyalty (Gremler & Brown, 1999).

Thus, by adapting and extending Ordenes et al. (2014) and McColl-Kennedy et al., 2019, we propose four elements of value co-creation mechanisms that influence firms' CX performance. These are activities (A), resources (R), contexts (C), and interactions (I), which we term the ARCI value co-creation model. We propose that the ARCI model constitutes the migration mechanisms that will influence the changes within firms' CX performance over time and which can be used as tools for dynamically managing firms' CX performance. Specifically, we define resources as including the consumers' personal resources and the focal firm's resources. For example, company resources may include employees, service competencies, facilities, equipment, and software systems. Activities address the cognitive and behavioral performance or the active carrying out of tasks/processes, while actions are related to value co-creation and include a firm's activities (e.g., providing room service), customers' activities (e.g., ordering room service), and other actors' activities. Interactions are the ways in which individuals engage with others in their consumption context, including the interaction between firms/service providers/frontline employees and customers, the interaction between the focal customer and other customers, and the interaction between the focal customers and other entities (platforms, systems, institutions). We note from McColl-Kennedy et al. (2012) that "activities" reflect the cognitive and behavioral performance of the active doing of things, while "interactions" reflect collaboration with others in the service network. Therefore, to highlight the role of interaction (and to remain consistent with previous research) we separate interactions from activities and view them as two distinct components in the ARCI model (Baxendale et al., 2015; Bitner, Booms, & Mohr, 1994; Gentile et al., 2007; McColl-Kennedy et al., 2012; 2019). The fourth component is context. Context includes the firm's specific contexts (e.g., service failure occasions, accidental events happening in the hotel), customers' specific contexts (e.g., business trips versus family vacations), and the situational/external environment contexts (e.g., the coronavirus pandemic affecting the global/local travel industries). Previous research shows that value co-creation depends on the context in which the service is generated (Grönroos & Voima, 2013; Ordenes et al., 2014). We contend that contexts can affect a customer's experience trajectories both positively and negatively.

Although the ARCI elements feature widely in the service literature, they tend to be absent from the CX literature. CX literature has not sought to explain firms' CX performance from the perspective of value co-creation (Galvagno & Dalli, 2014). We therefore aim to enrich the CX literature by introducing value co-creation and the ARCI components as the underlying process/migration mechanisms of firms' CX performance. This will shed light on the relevance of ARCI components to the changes in a firm's CX performance. We note that most of the value co-creation literature tends to focus on the design and development of goods/services, such as collaborative innovations in new product development, whereby customers interact with companies with respect to new product or service development (Hoyer et al., 2010; Sawhney, Verona, & Prandelli, 2005), interactive and support services (Bolton & Saxena-Iyer, 2009; Nambisan & Baron, 2007), co-production of services (Ballantyne & Varey, 2006), or both (Nambisan & Nambisan, 2008). What is absent in the value co-creation research is the explicit recognition of an experience-dominant/experience-centric logic. Consequently, there has been very little discussion of how the value co-creation process/mechanisms influence customers' perceptions of their experiences or a company's CX performance. This is a significant gap in both the CX and value co-creation literatures, especially given the attempts to bring the service logic/value co-creation concept into the CX management domain.

Finally, to respond to CX researchers' calls for new organizational models for CX management (Lemon & Verhoef, 2016), we extend the value co-creation perspective and propose the ARCI mechanism that includes four types of value co-creation elements as a means of better understanding and managing firms' CX performances. We further note that the four co-creation elements in the ARCI model (activities, resources, contexts, and interactions) can be understood as strategic mechanisms for positively and negatively influencing firms' CX performances in our research settings.

4.2.4 Proposing the Research Framework: the Trajectory of Firms' CX Performance

Following the discussion in section 4.1, we argue that knowledge gaps exist in the extant CX management theory in terms of offering insights into the strategies that managers might use to influence migration from different CX performance states. Nor does the theory explain how different migration strategies might ultimately affect firms' CX performance states. To bridge these gaps, we therefore start section 4.2.1 with a review of the CX literature that examines the nature of CX and CX performance. This is followed in section 4.2.2 with a review of the customer dynamics literature in which we develop the concept of the trajectory of firms' CX performance. In sections 4.2.3-4.2.4 we draw on these two conceptualizations and employ the lenses of dynamic perspective and value co-creation to infer CX performance states, service providers' migration across the distinct performance states, and the effective mechanisms for inducing migration. Through our review of the value co-creation literature, we develop value co-creation mechanisms as migration strategies that promote or suppress state migration. The primary goal of this study is to empirically understand the dynamic nature of the CX performance trajectory and the distinct effectiveness of the migration mechanisms.

From a dynamic perspective, we hold that the CX performance states are hidden, as they are unknown *a priori* and must be identified from the data. We characterize each CX performance state by the level of customers' perception of cognitive CX, affective CX, physical CX, and social CX as well by evaluating the rating score awarded by the customers. We model state migration using positive/negative ARCI mechanisms. Three critical tenets constitute our research framework for the trajectory of firms' CX performance.

(1) The CX Performance States. Through the literature review, we define CX as multidimensional in nature, involving the customer's perceived, subjective response to the experience providers. The customer's perceived response includes cognitive-rational, affective-emotional, social-relational, and physical-sensory responses. These four dimensions of CX perceptions provide a multifaceted view to shape firms' CX performance state. Moreover, we use the observed individual rating score as the indicator variable for firms' CX performance states. We hypothesize that the four dimensions of CX perceptions operate as covariates of the individual rating scores to determine a firm's current CX performance state. In short, we propose that firms' CX performances can change over time from lower to higher levels, represented by customers' higher and lower rating scores, which are determined by customers' evaluations of their perceived cognitive CXs, affective CXs, social CXs and physical CXs.

(2) Transition among CX Performance States. Because the unique combination of state variables (the four dimensions of perceived CX and customers' awarded experience rating score) determine a firm's CX performance state, migrations are determined by changes in the state variables. Employing a dynamic model can show how transient or sticky the different CX performance states are and the model allows for both gradual migrations and sharp transitions from one performance state to all others. To observe experience providers' switching patterns and the switching probabilities between these CX performance states over time, the providers' behaviors are assumed to underlie a first-order Markov process (Pfeifer & Carraway, 2000). In brief, any current performance state is only contingent on its state immediately prior to the current one and is independent of all earlier migration paths. The observed switching of firms' CX performance is a realization of a standard underlying matrix of switching probabilities.

(3) The Migration Mechanisms Influencing the Transition among States. We choose migration strategies that reflect the essential value co-creation elements in the service literature and propose an ARCI model to depict the migration mechanisms in our research framework for CX performance trajectories. A migration mechanism is the unique pattern of changes in state variables that leads to migration. In line with the extant value creation literature, we identify activities (A), resources (R), contexts (C), and interactions (I), reflecting the unique patterns of changes in the CX performance states. In the current study, the ARCI mechanisms are double-faceted and will exert distinct impacts on different transition/migration paths. We develop the positive ARCI mechanism from customers' positive comments/compliments and explicitly model upward migrations that are influenced by this mechanism. Similarly, we develop the negative ARCI mechanism from the customers' negative comments/complaints and propose its dynamic influences on downward migration patterns. We hypothesize that the positive mechanism will increase the probabilities of upward migrations, i.e., going from a lower to a higher state of CX performance. On the other hand, the negative migration mechanism will increase the probabilities of downward migrations, i.e., going from a higher to a lower state. **Figure 4.1** presents the research models from the dynamic perspective, which allows experience providers to change their latent states of CX performance across time points using the positive/negative mechanism derived from the value co-creation perspective.

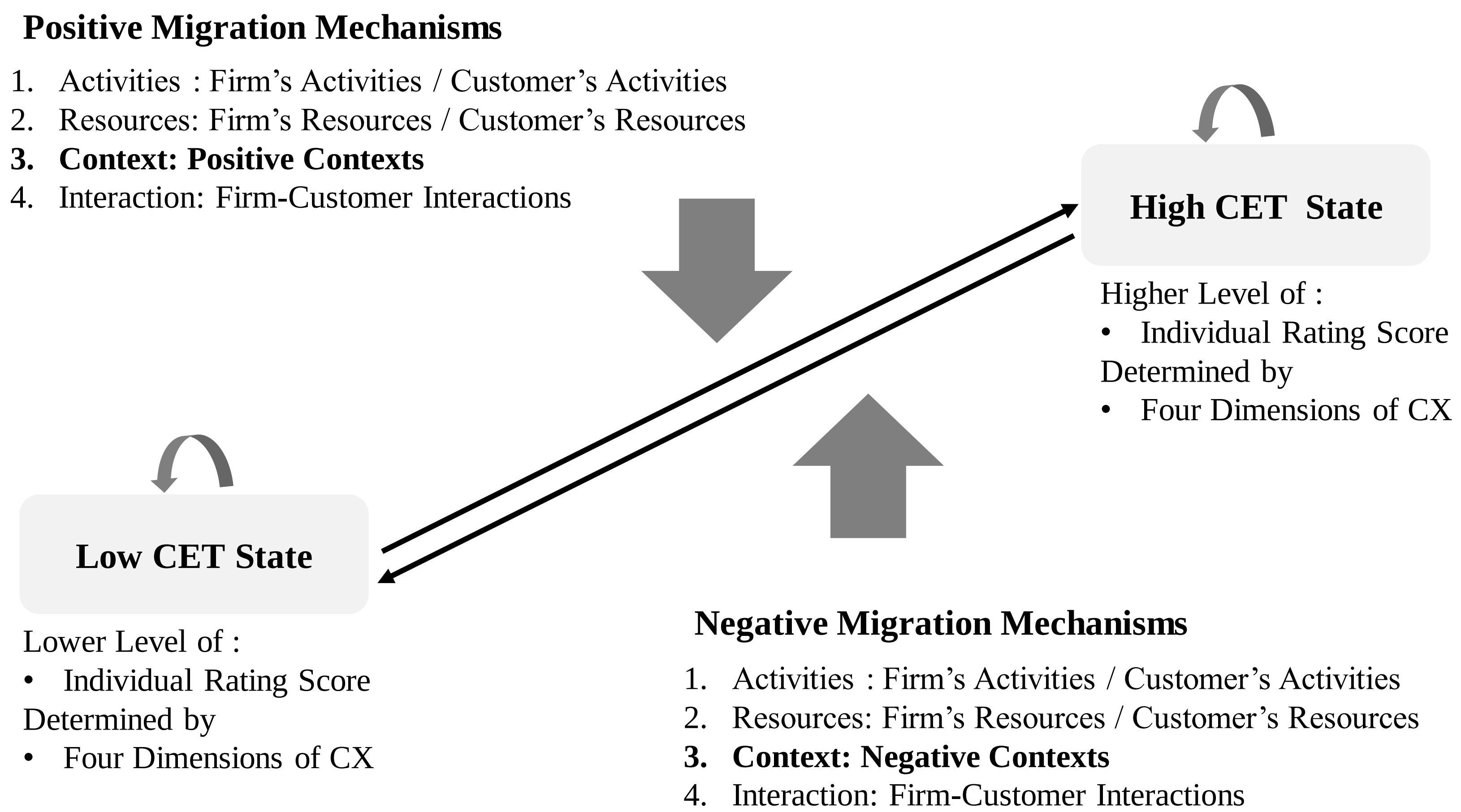


Figure 4.1 The Research Framework of Firms’ CX Performance Trajectories and Positive/Negative Migration Mechanisms

4.3 Methodology

4.3.1 Data

This current study uses longitudinal, unstructured, textual data from customers' verbatim reviews to generate new insights for understanding firm's trajectories of CX performance. It also offers practical assistance with the identification of the salient concepts in our research framework (Gopalkrishnan, Steier, Lewis, & Guszcza, 2012). Balducci and Marinova (2018) define unstructured data (UD) as a single data unit in which the information offers a relatively concurrent representation of the data point's multifaceted nature, without predefined numeric values. Its non-numeric characteristic means that UD lacks predefined numeric assignments for the constructs of interest, so researchers must conduct manual or automatic coding prior to the analysis. Moreover, a single unit of UD possesses multiple facets, each of which offers unique information, thereby enabling researchers to select and analyze the appropriate facets according to their specific research goals. Another characteristic of UD is concurrent representation. The simultaneous presence of the multiple facets of a single item of data, where each facet provides unique information, will allow a UD unit to simultaneously represent different phenomena. Thus, researchers can examine different research questions using a single UD unit based on the concurrent flow of these unique facets. Our aim in this research is to leverage the benefits of UD to disentangle the complexity surrounding the dynamic nature of CX and CX performance (Ordenes et al., 2014).

We first employ the web crawling technique and a Python algorithm to collect consumers' online reviews and rating scores from the Booking.com website. We collect guest reviewers' comments and rating scores related to 1,054 hotels listed in New York

City, resulting in a total of 131,566 comments and individual rating scores for the period from June 1 to August 30, 2019. New York City is, according to the most up to date statistics (2020) from the U.S Census Bureau population, the largest city in the US. It is also the top destination for international tourists and travelers, who have a multiplicity of travel purposes, which is not the case for many other tourism destinations. All NYC listings and their received ratings and the latest 300 reviews between June and August/2019 were crawled on the Booking.com website, where guests can leave their comments, both positive and negative, about their accommodation providers. This means that a single guest can separately, but simultaneously, state her compliments and complaints online regarding her service encounter with a given hotel. Our dataset contains longitudinal textual data and individual rating score metrics that combine qualitative and quantitative measures to determine the different levels of the CX performance states.

After completing the data collection process, the next decision concerns the choice of an appropriate research approach for operationalizing the focal concepts. Researchers in the CX domain have suggested that text mining and big data technologies can potentially offer better ways of measuring and managing CX (Keiningham et al., 2017; Lemon & Verhoef, 2016; McColl-Kennedy et al., 2019; Ordenes et al., 2014; Verhoef, Kooge, & Walk, 2016). The application of big data analytics and text-mining techniques involves the extraction of non-trivial, meaningful knowledge or patterns from unstructured text data. Aggarwal and Zhai (2012) define text mining as the analysis of data in natural-language texts, using a process that generally involves turning text into numbers to extract meaningful numeric indices from unstructured information. The numeric indices make the information accessible for further analysis or statistical and machine learning algorithms (Meyer et al., 2008; Sebastiani, 2002). Following Humphreys and Wang (2017) and Balducci & Marinova (2018), and using Berger et al. (2020)'s design for a text mining workflow, we describe how we gained important insights from the extensive big data that arise throughout a CX. By leveraging the characteristics of UD, we enter the second phase of data operationalization (section 3.2), which entails converting UD into numeric data. This phase involves extracting words and phrases from the guests' textual comments. coding the data, developing a custom dictionary for concepts that are not already included in the standard dictionary, conducting a dictionary-based analysis to convert the texts into quantifiable measures, and assessing the validity of the extracted text and measures.

4.3.2 Employing the Text Mining Technique and Dictionary-Based Analysis

The rapid emergence and growth of technology capable of analyzing vast amounts of unstructured data through text mining methods (Marr, 2017) has also made unstructured data increasingly prominent in the marketing literature (Balducci & Marinova, 2018). Balducci and Marinova (2018) suggest a three-process framework for implementing an unstructured data analysis in marketing research. Berger et al. (2020) provide a set of guidelines and procedures regarding text analysis workflow. In line with their suggestion, we adopt a five-step process that involves text extraction and dictionary development, the examination of the internal and external validity of the developed dictionary, the production of text analysis metrics, and the aggregation of individual-level numeric data to generate a firm-level dataset for modeling analysis.

According to Humphreys and Wang (2017), if the concept is relatively clear, the researcher can use a dictionary to measure the construct through a top-down approach. In principle, a dictionary-based approach entails using a set of rules to count the concepts based on the presence or absence of a particular word. For a dictionary-based analysis, researchers define and then calculate measurements that summarize the textual characteristics that represent the construct.

In our research, we measure the four dimensions of the CX perception under focus (perceived cognitive CX, affective CX, social CX, and physical CX) through use of the Linguistic Inquiry Word Count 2015 Dictionary, which is derived from existing psychometrically tested scales. These dimensions respond to several word categories in the LIWC dictionary, including affective, social, cognitive, perceptual (see, hear, feel), and biological processes (the body). A standardized dictionary such as the LIWC, which bases its measurement on the underlying psychological scales, can provide good construct validity (Pennebaker et al., 2015). However, no standardized dictionary is available for measuring the proposed ARCI value co-creation mechanism that is the focus of this study. Thus, it is necessary to create a custom dictionary. Adapting works of Balducci and Marinova (2018), Humphreys and Wang (2017), Marinova et al. (2018) as well as Perreault and Leigh (1989), the process we employ to develop the custom dictionary is presented in **Figure 4.2.**

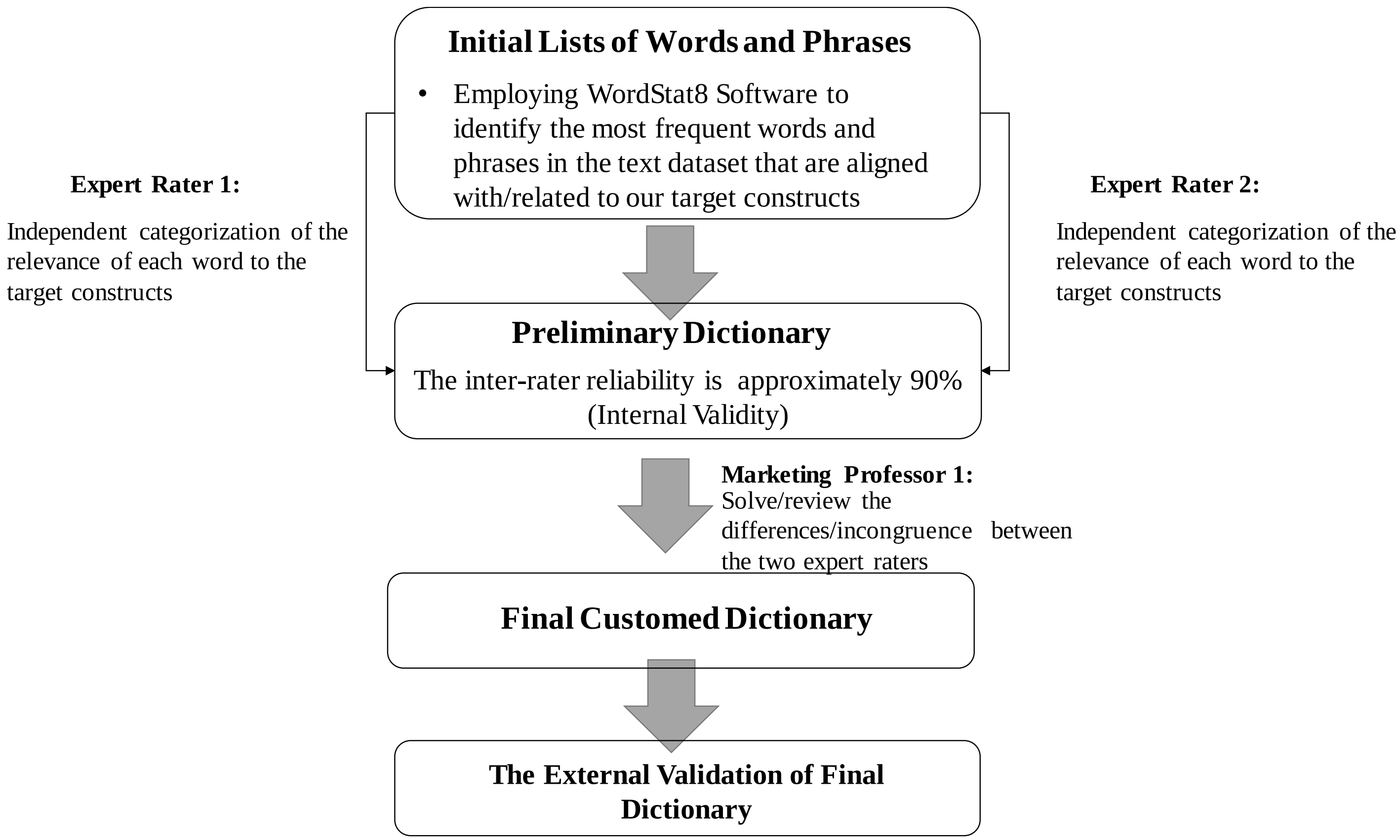


Figure 4.2 Dictionary Development and Validation

Leveraging the processing program WordStat8, we apply the text mining technique to extract words and phrases from the unstructured text data, separately considering the positive and negative comments from the same guest reviewers. Then, we provide a list of words and phrases extracted from the compliments (positive comments) and complaints (negative comments) to two experts with doctoral degrees in linguistics from which they develop a customized value co-creation dictionary for the Booking.com context. This custom dictionary captures all the value creation elements in our ARCI model, including firm's/customer's activities, firm's/customer's resources, positive/negative contexts, and positive/negative interactions between firms and customers. We develop a coding scheme pertinent to our field setting in that it integrates the seven CX evaluation criteria available on Booking.com, namely: (1) staff; (2) facilities; (3) cleanliness; (4) comfort; (5) value for money; (6) location; and (7) free Wi-Fi. The criteria of staff, facilities, location, and free Wi-Fi are assigned to the "firm's resources" categorization; the criteria of cleanliness and comfort are categorized as "firm's activities"; and value for money is allocated to "customer's resources". The goals of introducing the seven real-world CX evaluation criteria are two-fold. First, they add managerial insights for the ARCI mechanism via the weaving of real-world variables with theoretical concepts. Second, these real-world variables are practical management actions over which the experience providers have direct control. For example, hotel managers could take action to improve staff training, the quality of the hotel's facilities, the cleanliness and comfort of the rooms, and the stability of free Wi-Fi, all of which will directly affect guests' perceptions of these variables and thereby influence the rating scores.

The logic of the coding schema is based on our definition of the ARCI elements in this current study. First, we define **A**ctivities as firms' activities and customers' activities. The former addresses the cognitive and behavioral performance of hotels; the latter represents the guests actively doing things; the actions of both parties are related to value co-creation. We assign two of Booking.com's evaluation criteria to firm's activities: cleanliness and comfort. We argue that the cleanliness and comfort criteria represent a firm's performance of its core activities in the hospitality industry. The basic coding rule given to the coders regarding Activities is that the word and phrases appearing in the review content must be related to hotels' and customers' actions or the performance of those actions.

Secondly, the component of **R**esources is also categorized as both firms' resources and customers' resources. We assign four criteria on Booking.com to firms' resources: staff, facilities, location, and free WIFI. The basic rule given to the linguist coders for resources is that it relates to words and phrases appearing in the review contents concerning the hotel's facilities, amenities, or software, or the customers' resource investment such as time, money, or other physical/non-physical resources.

Thirdly, the component of **C**ontexts includes the firm's specific contexts (e.g., accidental events happening in the hotel), customers' specific contexts (e.g., a family vacation to celebrate a wedding anniversary), and situational/external environment contexts (e.g., a national strike affecting the local transportation network). The coding rule regarding contexts is that it concerns words and phrases related to contextual factors (music, atmosphere, sounds, smell) in the hotel or its external situation, the environment, or any events (e.g., noise, fire alarm caused by other guests, bad smell, tobacco smell coming from next-door neighbor).

Finally, the fourth component of **I**nteractions is coded as the words and phrases appearing in the review content that are related to interactions; these include guests' perceptions of their interactions (e.g., friendly staff, supportive personnel) and how the interactions are carried out between experience providers and experience receivers (e.g., helpful, friendly, supportive). **Table 4.1** presents our coding schema that includes six major categories and 13 subcategories, which covers our proposed ARCI elements and experience evaluation criteria on Booking.com.

Table 4.1 Data Coding Schema for Developing the Custom Value Co-creation Dictionary

ARCI	Major Categories	Sub-Categories
A: Activities	1. Firm's Activity	(1) Cleanliness *(the evaluation criterion from Booking.com)* (2) Comfort *(the evaluation criterion from Booking.com)* (3) Service (4) Other Activities
	2. Customer's Activity	
R: Resources	3. Firm's Resources	(5) Staff *(the evaluation criterion from Booking.com)* (6) Facilities *(the evaluation criterion from Booking.com*) (7) Location (*the evaluation criterion from Booking.com*) (8) Free WIFI (*the evaluation criterion from Booking.com*) (9) Amenities/consumables (foods, drinks, towels) (10) Other Resources
	4. Customer' Resources	(11) Value for Money (*the evaluation criterion from Booking.com*) (12) Time (13) Other Resources
C: Context	5. Contexts	
I: Interaction	6. Interaction	

To produce the initial dictionary, the two linguists independently evaluated and categorized the relevance of each word and phrase on the list, using the provided coding schema. We follow Berger et al. (2020)'s suggestion to conduct an internal dictionary validation. We first assess the inter-rater consistency and retain those words/phrases that were consistently evaluated by the linguistic experts as matching the nine categories/13 subcategories in our coding schema. We then invite a marketing professor to review the words/phrases that were inconsistently judged by the two linguistic experts. The initial word lists for the six categories/13 sub-categories were updated according to the following rule: if two of the three coders agreed that the word belonged to that category, include it; if not, exclude it (Humphreys, 2010). We calculate the level of overall agreement across the six categories, finding that each exceeds the 0.9 threshold (Rust & Cooil, 1994). Our final value co-creation dictionaries could therefore operate as a positive mechanism from the guest reviewers' positive (compliment) comments and a negative mechanism from their negative (complaint) comments, as presented in **Table 4.2**. The developed dictionary includes 30 concepts, presented as 15 positive ARCI elements extracted from positive comments and 15 negative ARCI elements extracted from negative comments.

Table 4.2 Examples of the Self-Developed Dictionary

ARCI Elements from Positive Comments	Example of Words and Phrases	#of words /phrases in categories
Firm's Resources Extracted From Positive Comments		
1. Staff	bar staff, check-in staff, cleaning staff, door staff	153
2. Facilities	air conditioning, ambiance, amenities, elevator, bathroom	370
3. Location	centrally located, close proximity, close to subway	257
4. Free WIFI Resources	free WiFi internet, wifi	8
5. Other Resources	room view, water bottle, breakfast buffet, coffee and snacks	64
Customer's Resources Extracted From Positive Comments		
6. Value for Money	cheap, cost, expensive, free, free of charge	40
7. Time	hour, hours, mins, minute, minutes, nights	23
8. Other Resources	bags, camera, car, guest, luggage	16
Firm's Activities Extracted From Positive Comments		
9. Cleanliness	clean, clean and neat, cleaned every day, cleaning, cleanliness	61
10. Comfort	cozy, extra comfy, small but comfortable	59
11. Service	customer service, housekeeping, maid service, room service	100
12. Other Activities	appointed, looked after, make our stay	24
13. Customer Activities Extracted from Positive Comments	Booking, check in and check out, check in early	176
14. Positive Contexts Extracted from Positive Comments	absolutely amazing, absolutely perfect, amazing awesome	545
15. Positive Interactions Extracted from Positive Comments	helpful staff, friends, helpful, incredibly helpful, friendly staff	97

ARCI Elements from Negative Comments	Example of Words and Phrases	# of words / phrases in categories
Firm's Resources Extracted From Negative Comments		
1. Staff	bar staff, check in staff, cleaner, cleaning lady	35
2. Facilities	bar and restaurant, bar fridge, bathroom, bathtub	446
3. Location	across the road, across the street, airport, areas, central	53
4. Free WIFI Resources	free wifi, internet, internet connection, website, wifi connection	17
5. Other Resources	complimentary coffee, continental breakfast, ice bucket, key	128
Customer's Resources Extracted From Negative Comments		
6. Value for Money	amount of money, bill, charge, credit card, deal, deposit, facilities fee	78
7. Time	after days, after hours, couple of days, day and night, days	57
8. Other Resources	large suitcases, luggage, personal photos, stuff, previous guests	29
Firm's Activities Extracted From Negative Comments		
9. Cleanliness	bit dirty, dirty, room was not clean, room was not cleaned	22
10. Comfort	bit uncomfortable, extremely uncomfortable	8
11. Service	customer service, housekeeping, poor quality, room was not ready, wrong room, extremely slow	83
12. Other Activities	advertised, control, décor, fit, fix, informed, maintenance	57
13. Customer Activities Extracted From Negative Comments	checking, checkout, choice, coming, sleep, booking, stayed	189
14. Negative Contexts Extracted From Negative Comments	bad smell, bad thing, difficult, extremely hot, extremely loud, fault, extremely noisy, awful, big problem, worst hotel	294
15. Negative Interactions Extracted From Negative Comments	bit rude, rude, staff was rude, couple, kids, family, rude staff	26

Furthermore, by integrating the finalized custom dictionary with the standardized dictionary (the default LIWC 2015 Dictionary), we apply a dictionary-based approach using LIWC software to transfer unstructured text data into structured numeric data for further analysis. We use a default dictionary to assess the overall comments, including positive and negative ones, thereby generating four CX variables: cognitive CX; affective CX; social CX; and physical CX. We use the custom positive (negative) value co-creation dictionaries to assess the positive (negative) comments; this generates 15 positive and 15 negative ARCI variables. Hence, the total of 30 variables that comprise the positive and negative migration mechanisms. During its operation, the LIWC 2015 software accesses our textual dataset by one target word at a time. As each target word is processed, the three dictionaries' files are searched for a match with the current target word. If the target word matches a dictionary word, its appropriate word category scales are incremented. As the original textual datasets are being processed, the counts for various structural composition elements are also incremented. We then receive the final numeric dataset. For each reviewer and his/her comments, there are 35 output variables. These are the rating score, the four dimensions of CX, 15 positive value co-creation elements, and 15 negative value co-creation elements.

To examine the validity of our developed value co-creation dictionary, we conduct a correlation analysis as suggested by Humphreys and Wang (2017). We use random subsets of the data upon which we repeat the dictionary-based analyses to produce quantitative sub-datasets, hence conducting descriptive statistics analysis. The results of the two sub-datasets are congruent. To further ensure external validity, we follow Berger et al. (2019)'s suggestions regarding the prediction of key performance measures (Fossen

& Schweidel, 2019). We include numeric variables derived from the Booking.com dataset in the regression model to predict the key outcome of the reviewers' rating score. We conclude that the predictive validity of the results is established because the text-based constructs (the four dimensions of CX perception and the positive and negative mechanisms) are linked to the key performance measures. The results show that, based on the significant regression coefficients, the particular constructs are theoretically linked to the performance metric of the rating score. Finally, according to Berger et al. (2019), text analysis often uses large-scale naturally occurring data and thus tends to have a relatively high degree of external validity in comparison to lab experiments. We believe that, in the current study, the standardized and developed dictionaries and the numeric metrics of our focal constructs achieve both internal reliability and external validity.

After converting the text into numeric metrics and assessing the construct validities, we conduct the final process of the data aggregation; this is aimed at transforming the individual reviewers' CX perceptions or evaluations into the hotels' CX performance at firm-level. We separate the 3-month timeframe of our dataset (June 1 to August 30, 2019) into 13 separate weeks. Hence, the first timepoint is week 1 (June 1 to June 7 inclusive) and the last timepoint is week 13 (August 24 to August 30 inclusive). We calculate each hotel's weekly average values for the 35 variables for each of the 13 consecutive time periods. After omitting hotels with missing datapoints during any of the 13 weeks, we finally generate a panel database structure containing the 1,019 hotels' weekly average rating scores and 35 time-varying variables (i.e., the perceived CX performances and value co-creation mechanisms).

4.3.3 Empirical Model Specification

Previous empirical research has noted the flexibility of the Hidden Markov Model (HMM) as a means of uncovering latent relationship states from observed customer behaviors (Luo & Kumar, 2013; Netzer et al., 2008; Zhang et al., 2016). The HMM is useful for studying relationships in a dynamic setting because it describes the latent relationship according to discrete states at any given point in time. It can also uncover customer migration patterns across states and identify the variables responsible for migrations (Zhang et al., 2016). We thus choose to employ HMMs to infer our latent states of firms' CX performance, track firms' migration across CX performance states, and identify the most effective CXM strategies for inducing migrations. HMM can identify the number of CX performance states, allow firms to migrate freely across different performance states, and assess the effectiveness of each migration mechanism on the migration path.

We account for hotels' CX performance dynamics through a nonhomogeneous HMM (Netzer et al., 2008), in which the states are defined by a given rating score and four perceived dimensions of CX. The nonhomogeneous HMM will simultaneously capture the rating dynamic, the short-term effects of perceived CXs on firm CX performance, and the long-term effects exerted by the value co-creation mechanisms on migrating firm CX performance. In HMM, the ARCI elements can have "regime-shifting" effects on the rating score and CX performance states, thus providing an approach for capturing their long-term effects.

An HMM is a Markov process with unobserved states. In our application, the hidden states represent different levels of firm CX performance combined with the rating scores given by reviewers. They are determined by different levels of reviewers' cognitive, affective, social, and physical CX perceptions. Firms stochastically transition among these states through a first-order Markov process. The transitions between states are functions of the ARCI migration mechanisms. For example, the interaction between service providers and customers may move the firm from a lower to a higher CX performance state. Thus, the HMM model can capture the effect of firm-customer interactions through their impact on transition probabilities.

In the HMM, we assume that the probability distribution of Y_{it} depends on the realization of an unobserved (latent/hidden) discrete stochastic process S_{it}, with a finite state space {1,…, K}. Hence, while we can observe Y_{it} directly, we can only observe S_{it} indirectly through its stochastic outcome or noisy measure Y_{it}. In the HMM, the state membership S_{it} is assumed to satisfy the Markov property, such that $P(S_{it+1}|S_{it}, S_{it-1}, \ldots S_{i1})=P(S_{it+1}|S_{it})$. The HMM for the CX performance of $Hotel_i$ transitioning among K states over T periods can be written as follows:

$$P(Y_{i1},Y_{i2},\ldots Y_{iT})=\sum_{s_1=1,2,\ldots K} P(S_{i1} = s_1) \prod_{t=2}^{T} P(S_{it} = s_t|S_{it-1} = s_{t-1}) \prod_{t=1}^{T} P(Y_{it}|S_{it} = s_{it})$$

As presented in the above equation, there are four main components of the HMM, as follows.

(1) The Initial State Distribution

$P(S_{i1}=s_1), s_1=1,2\ldots K$, which may be represented by a $1\times K$ row factor π. Let s denote a latent CX performance state (s=1,2,3,4, …, K) and π_{is} denote the probability that $Hotel_i$ is in state s during the first period of our dataset, where $\sum_{s=1}^{K} \pi_{is} = 1$.

(2) The Transition Probabilities

$P(S_{it}=s_{it}|\ S_{it-1}=s_{it-1})$ for s_{t+1}, $s_t=1,2,\ldots$, K, which may be represented by a K× K transition matrix Q. The HMM transition matrix $Q_{i,t-1\to t}$ denotes the probability that Hotel$_i$ will migrate from one CX performance state to each other state over time, modeled as a Markov process Q_{it}, thus:

	State at t					
State at t-1	1	2	3	...	$S-1$	S
1	$W_{it1,1}$	$W_{it1,2}$	$W_{it1,3}$	...	$W_{it1,S-1}$	$W_{it1,S}$
2	$W_{it2,1}$	$W_{it2,2}$	$W_{it2,3}$	...	$W_{it2,S-1}$	$W_{it2,S}$
3	$W_{it3,1}$	$W_{it3,2}$	$W_{it3,3}$	...	$W_{it3,S-1}$	$W_{it3,S}$
.	.	.	.		.	.
.	.	.	.	...	.	.
.	.	.	.		.	.
$S-1$	$W_{itS-1,1}$	$W_{itS-1,2}$	$W_{itS-1,3}$	...	$W_{itS-1,S-1}$	$W_{itS-1,S}$
S	$W_{itS,1}$	$W_{itS,2}$	$W_{itS,3}$	...	$W_{itS,S-1}$	$W_{itS,S}$

$W_{itss'}$=P($S_{it}\ = s'\ |S_{it-1}\ = s$) is the conditional probability that a hotel will move from state s at time t-1 to state s′at time t and $\forall s, s'$, $\Sigma_{s'} W_{itss'}\ = 1$. These transition probabilities might be influenced by several factors (i.e., the ARCI value co-creation elements) at time t-1. We define each transition probability as a function of the migration mechanisms using a logit specification to ensure that $0\leq W_{itss'} \leq 1$. That is, $W_{itss'}$= $\frac{e^{Xit-1'\gamma s}}{1+\ \Sigma_{s=1}^{S-1}\ e^{Xit-1'\gamma_s}}$, where X_{it-1} is a vector of the migration mechanisms affecting the transition between CX performance states and γ_s is a state-specific vector of the response parameter that measures the impact of each migration element on the transition probability $W_{itss'}$. In our transition matrix specification, we include both positive and negative mechanism variables so that we can compare the relative effects between all value co-creation elements for each migration path and identify the most effective migration strategy for each path.

(3) The State-Dependent Distribution

The state-dependent distribution of observed activity $P(Y_{it}|S_{it}=s_{it})$, $S_t=1,2,\ldots,K$ may be represented by a $K\times K$ matrix $M_{i\tau}$ that has the elements $P(Y_{it}| S_{it}=s_t)$ on the diagonal and zeroes on the off-diagonal. In the HMM, given $Hotel_i$'s state S_{it}, the observed average rating score in $Hotel_i$ (Y_{it}) is a noisy measure and a probabilistic outcome of the state. The $P(Y_{it}|S_{it})$ depends only on the current state, and the conditional probabilities $P(Y_{it}|S_{it})$ are independent over time. In our research, $Hotel_i$'s state-dependent distributions are specified as a generalized linear model with four covariates, where the regression parameters are state dependent. We have one dependent variable of the hotels' received (weekly average) rating score and four time-varying covariates (the four dimensions of perceived CX) given by the 4 x 1 vector X_{it}, so the state-dependent distribution can be written as $m_{its}=P(Y_{it}|S_{it}=s_t, X_{it})$. We can define a matric M_{it} that collects the state probabilities of $Hotel_i$ at time t as a K×K diagonal matrix:

$$M_{it}=\begin{bmatrix} m_{it1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & m_{itK} \end{bmatrix}$$

(4) The Likelihood Functions

Finally, we combine the initial state distribution, the transition matrix, and the state-dependent distribution to form the HMM likelihood function of observing the weekly average sequence of observations. We can write the HMM likelihood function for $Hotel_i$ as follows: $L_{iT}=P(Y_{i1}, Y_{i2}, \ldots Y_{iT})= \pi M_{i1}QM_{i2}\ldots QM_{iT}\iota$, where π, M_{it}, and Q are defined as the initial state distribution, the matrix of state-dependent distributions, and the transition probabilities matrix, respectively, and ι is a $K\times 1$ vector of ones. The likelihood function is used to describe the evolutionary process of HMM. The process starts with $Hotel_i$ belonging to a particular latent CX performance state, which follows the initial state distribution, π. Given $Hotel_i$'s state in period 1, $Hotel_i$ performs in a particular manner, as described by the probability M_{i1}. Next, $Hotel_i$ transitions from the performance state at time 1 to the next state at time 2, as described by the transition probability Q. Subsequently, given the state that $Hotel_i$ transitioned to at time 2, M_{i2} captures $Hotel_i$'s guests' behaviors in period 2, followed by another transition matrix, Q. This process repeats until the final state of $Hotel_i$ in period T is reached.

Finally, we use the software program Latent Gold 5.1 (Vermunt and Magidson 2015), which uses a special variant of the EM algorithm called the forward-backward or Baum-Welch algorithm. We employ Latent Gold to estimate an HMM characterized as non-homogeneous (integrating covariates in the transition probability matrix). To formulate an HMM in Latent Gold, the observed variables Y_{it} (here, the received rating scores of $Hotel_i$) must be selected as the indicators. Next, the covariate variables that correspond to the indicator variable are selected. In our setting, the covariate variables are the four CX variables (the cognitive, affective, physical, social dimensions) and all the value co-creation elements. We include the four dimensions of perceived CX that operate as migration mechanisms, i.e., they impact on the state-dependent distribution and the value co-creation elements, thereby impacting on the transition probabilities.

We define the impacts exerted on the transition probabilities matrix by the migration mechanisms as long-term effects. When the covariates are included in the transition probabilities, they are postulated to create a regime shift in firm CX performance and exert a long-term effect, whereas the covariates that are included in the state-dependent distribution affect the CX performance (received rating scores) in the current period and therefore have a short-term impact.

In general, HMM has two main components. The first component is the stochastic state dependent distribution; given a particular state, the observations are stochastically determined. For example, in our case, the observations of different levels of rating scores are determined by the different levels of latent states of firms' CX performances. We hypothesize that the four CX-related covariates will exert a short-term effect that influences firm CX performance (received rating scores) in the current state. The second component is a state Markovian evolution, which represents how the HMM model can transition from one state to another according to a set of transition probabilities. We hypothesize that the double-faceted migration mechanisms will influence the transition probabilities and we define these impacts as long-term effect. We argue that a switching behavior in the dataset will take longer than a state-staying behavior to be observed by the researcher. Thus, in this research, we define the effects exerted by migration mechanisms as long-term effects, which will cause a change in the firm's CX performance state. We label the ARCI mechanisms that seek to promote/suppress state migrations as positive/negative migration mechanisms that will enhance/deteriorate firms' CX performances.

4.4 Results

4.4.1 Descriptive Statistics and Model-Free Evidence

Tables 4.3 to Table 4.6 present the descriptive statistics and correlation coefficient matrices of our focal variables. Our dataset includes a total of 131,556 comments from all hotels listed in NYC on Booking.com, collected over a three-month timeframe from June to August 2019. We separate the 3-month timeframe of our dataset (June 1 2019 to August 30 2019) into 13 weeks, generating a total of 10,935 (weekly average) datapoints for our focal hotels. The first timepoint is labeled as week 1 (from June 1 to 7) and the last time stamp is week 13 (from August 24 to 30). The focal hotels have weekly average values of the corresponding variables for 13 consecutive weeks. These average values comprise the weekly average rating scores and the following time-varying variables: the four dimensions of perceived CX performances (affective CX, cognitive CX, social CX and physical CX) and the ARCI mechanism variables (activities, resources, contexts, and interactions). These compose the positive migration mechanism and the negative migration mechanism.

Table 4.3 The Descriptive Statistics of CX Performance State Variables

Variables of CX Performance States	Min	Max	Mean	S.D
Rating_Score	2.50	10.00	8.26	1.09
Affective_CX	0.00	33.34	6.86	4.63
Cognitive_CX	0.00	58.34	7.14	4.97
Social_CX	0.00	64.29	7.51	5.83
Physical_CX	0.00	37.50	3.44	2.64

Table 4.4 The Descriptive Statistics of Migration Mechanism Variables

Variables of Positive Migration Mechanism	Min	Max	Mean	S.D	Variables of Negative Migration Mechanism	Min	Max	Mean	S.D
Positive Firm's Activities	**0.00**	**54.17**	**2.29**	**3.86**	**Negative Firms' Activities**	**0.00**	**33.85**	**0.97**	**2.07**
1. Cleanliness	0.00	54.17	1.61	3.29	1. Cleanliness	0.00	25.00	0.25	0.99
2. Comfort	0.00	25.00	0.11	0.76	2. Comfort	0.00	16.67	0.08	0.60
3. Service	0.00	50.00	0.54	1.79	3. Service	0.00	33.85	0.34	1.43
4. Firm's Other Activities	0.00	10.00	0.03	0.27	4. Firm's Other Activities	0.00	16.67	0.29	0.83
Positive Firm's Resources	**0.00**	**100.00**	**21.11**	**12.77**	**Negative Firm's Resources**	**0.00**	**62.50**	**8.55**	**7.25**
5. Staff	0.00	60.00	2.65	4.05	5. Staff	0.00	33.33	0.10	0.90
6. Facilities	0.00	57.69	6.21	5.80	6. Facilities	0.00	62.50	6.74	6.34
7. Location	0.00	100.00	10.57	11.15	7. Location	0.00	50.00	0.52	2.09
8. Free Wifi	0.00	33.33	0.07	0.67	8. Free Wifi	0.00	25.00	0.24	1.37
9. Firms' Other Resources	0.00	50.00	1.61	3.37	9. Firms' Other Resources	0.00	51.39	0.96	2.11
Positive Customers' Resources	**0.00**	**50.00**	**1.23**	**2.33**	**Negative Customers' Resources**	**0.00**	**53.13**	**1.75**	**3.09**
10. Money	0.00	50.00	0.61	1.83	10. Money	0.00	52.09	0.88	2.70
11. Time	0.00	25.00	0.35	0.93	11. Time	0.00	14.06	0.62	1.17
12. Customers' Other Resources	0.00	18.28	0.27	1.05	12. Customers' Other Resources	0.00	12.50	0.26	0.76
13. Positive Customers' Activities	**0.00**	**50.00**	**1.91**	**2.39**	**13. Negative Customers' Activities**	**0.00**	**54.55**	**1.93**	**2.63**
14. Positive Contexts	**0.00**	**56.76**	**7.74**	**6.51**	**14. Negative Contexts**	**0.00**	**53.34**	**3.05**	**4.64**
15. Positive Interaction	**0.00**	**50.00**	**1.94**	**3.11**	**15. Negative Interactions**	**0.00**	**12.50**	**0.22**	**0.63**

Table 4.4 shows that the affective, cognitive, and social dimensions of CXs have relatively higher mean values (6.86, 7.14, and 7.51 respectively) and standard deviation values (4.63, 4.97, and 5.83 respectively) than the physical dimension of CX (3.44 of mean value and 2.64 of S.D) . Moreover, **Table 4.4** shows that the components of firms' activities, firm's resources, contexts, and interactions in the positive mechanism express higher mean values (2.29, 21.11, 7.74, 1.94 respectively) and standard deviation values (3.86, 12.77, 6.51, 3.11 respectively) than the mean values (0.97, 8.55, 3.05, 0.22 respectively) and standard deviations (2.07, 7.25, 4.24, 0.63 respectively) of the same components from the negative mechanism.

Table 4.5 The Correlation Coefficients among Rating Score and Four Dimensions of CX

	Rating Score	Affective CX	Cognitive CX	Social CX	Physical CX
Rating Score	1.00	.373**	.089**	.182**	0.02
Affective CX	.373**	1.00	.104**	.182**	.029**
Cognitive CX	.089**	.104**	1.00	.384**	.071**
Social CX	.182**	.182**	.384**	1.00	.075**
Physical CX	0.02	.029**	.071**	.075**	1.00

Note: * means significant at 5% and ** means significant at 1%

Table 4.6 The Correlation Coefficients among Rating Score and Positive/Negative Mechanisms

	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Rating Score	1.00	.097**	0.01	.092**	-0.01	.191**	.090**	-.098**	-.117**	-.045**	-.025**	-.067**	-.118**
2.Positive Firm's Activities	.097**	1.00	.040**	-.051**	.023*	.074**	.044**	-0.01	.079**	.042**	.056**	.094**	.030**
3. Positive Firm's Resources	0.01	.040**	1.00	-.106**	-.056**	.263**	.104**	.086**	.298**	.085**	.146**	.204**	.027**
4. Positive Customers' Activities	.092**	-.051**	-.106**	1.00	.065**	0.00	-.055**	-0.00	-.022*	0.02	-0.01	-.035**	0.01
5. Positive Customers' Resources	-0.01	.023*	-.056**	.065**	1.00	.021*	-.026**	.022*	.051**	-0.00	-0.01	.076**	-0.01
6. Positive Contexts	.191**	.074**	.263**	0.00	.021*	1.00	.089**	-0.00	.091**	.025**	.061**	.073**	-0.02
7. Positive Interactions	.090**	.044**	.104**	-.055**	-.026**	.089**	1.00	-0.01	.066**	0.00	.066**	.066**	-0.01
8. Negative Firm's Activities	-.098**	-0.01	.086**	-0.00	.022*	-0.00	-0.01	1.00	.034**	.057**	.042**	-.024*	.030**
9. Negative Firm's Resources	-.117**	.079**	.298**	-.022*	.051**	.091**	.066**	.034**	1.00	.036**	.031**	.384**	.042**
10. Negative Customers' Activities	-.045**	.042**	.085**	0.02	-0.00	.025**	0.00	.057**	.036**	1.00	.052**	0.01	.032**
11. Negative Customers' Resources	-.025**	.056**	.146**	-0.01	-0.01	.061**	.066**	.042**	.031**	.052**	1.00	-0.01	0.02
12. Negative Contexts	-.067**	.094**	.204**	-.035**	.076**	.073**	.066**	-.024*	.384**	0.01	-0.01	1.00	0.02
13 Negative Interactions	-.118**	.030**	.027**	0.01	-0.01	-0.02	-0.01	.030**	.042**	.032**	0.02	0.02	1.00

Note: * means significant at 5% and ** means significant at 1%

Table 4.5 shows that the affective dimension of CX has the strongest association with the rating score. **Table 4.6** proves that there are positive associations among positive mechanisms and the rating scores as well as negative associations among the negative mechanisms and rating scores.

We then depict the general trends in the dataset in **Figures 4.3** to **4.4.** First, **Figure 4.3** presents the mean values of perceived CXs and the rating scores over the 13-week study period. We can see heterogeneities in the collectively perceived affective CX, cognitive CX, social CX, and physical CX, and there are also fluctuations in the customers' average rating scores over the 13-week time span. We further plot the trends of the mean values of positive and negative ARCI elements in **Figure 4.4.** We observe that, although the trends of the ARCI mechanisms are relatively static, the resource and context elements still exhibit fluctuations over time.

Our goal is to parcel out the dynamic nature of firms' CX performance, expressed by the rating score given by their customers and the customers' perceived CXs, and study the influences of the different migration mechanisms that drive such dynamic CX performance.

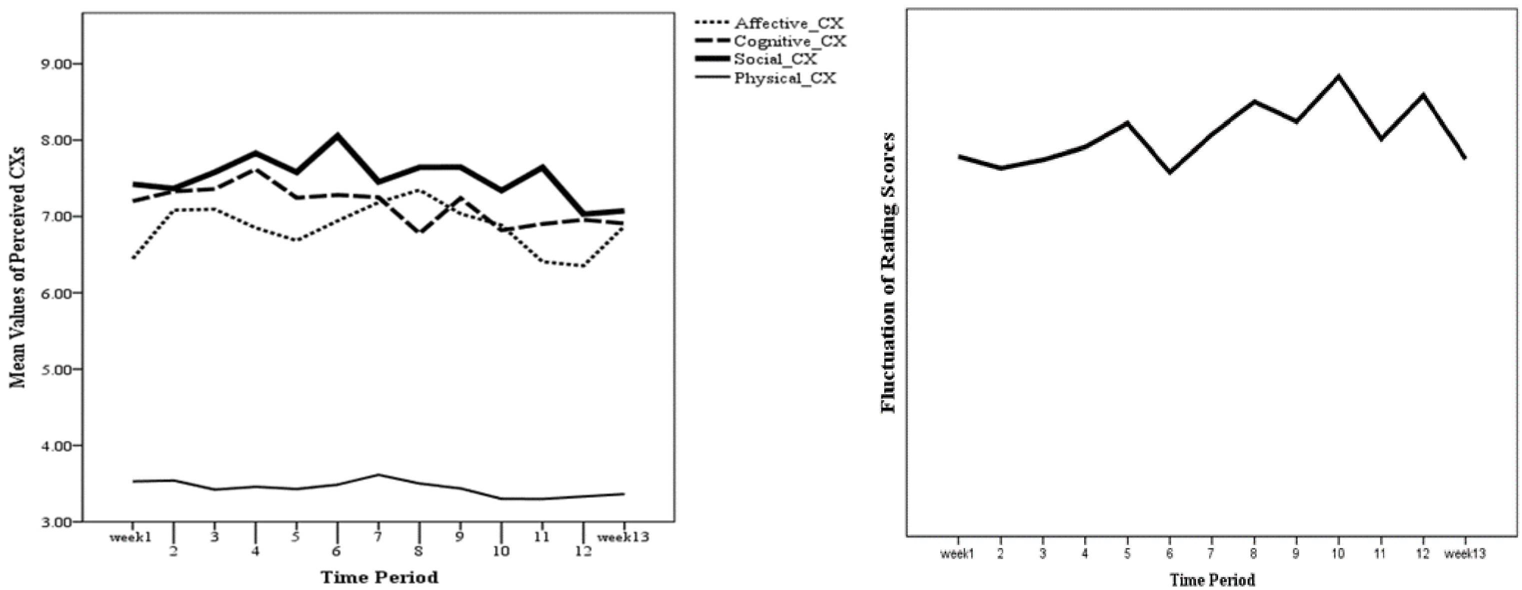


Figure 4.3 Trends in the Perceived Customer Experience and Rating Score over Time

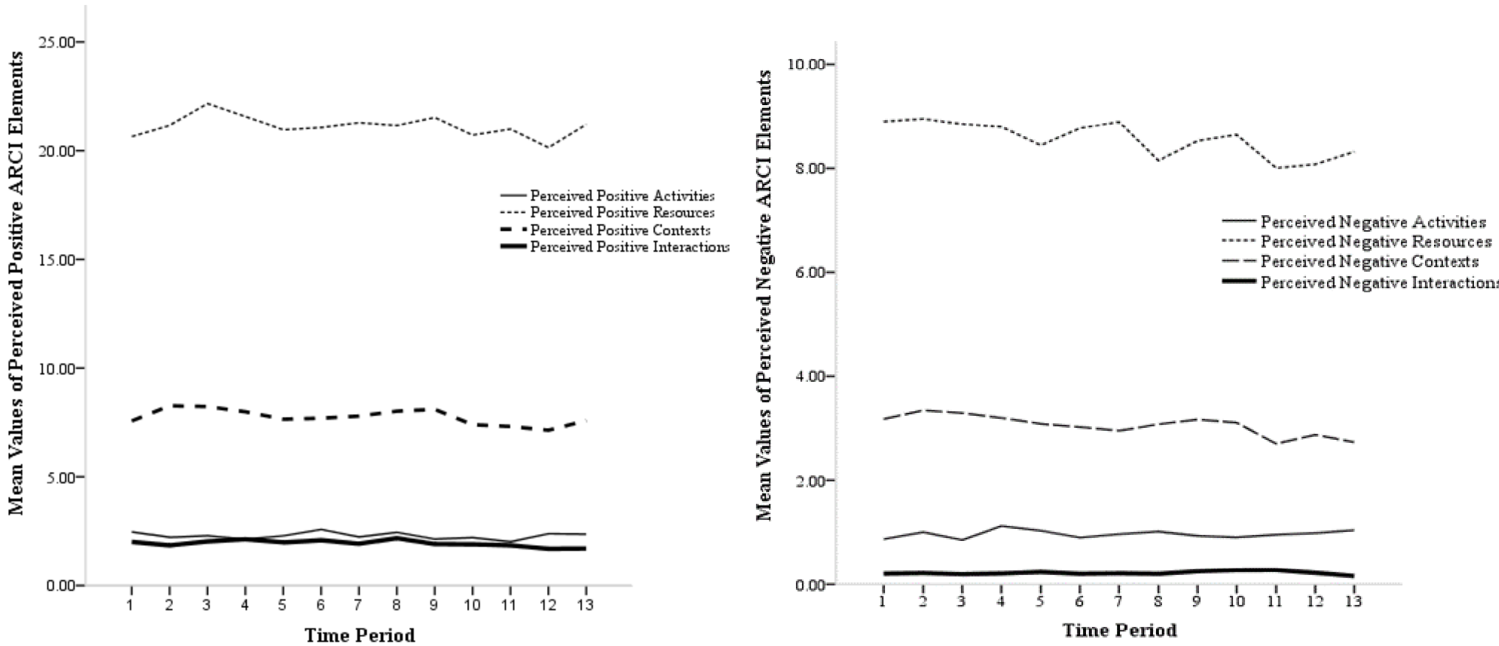


Figure 4.4 Trends in the Perceived Positive and Negative ARCI Elements over Time

4.4.2 Empirical Results

4.4.2.1 HMM Results for the CX Performance States

We possess no *a priori* knowledge about the exact number of CX performance states, so we estimate two-state to five-state models, with the full set of migration strategies, and select the one that offers the best fit. We compare various information criteria across these solutions to determine the most appropriate number of states. Our minimum numbers of BIC (Bartolucci et al., 2014) and CAIC (Netzer et al., 2018) suggest an HMM with 4 hidden states. This finding is reinforced by the device information criterion (DIC), which accounts for model complexity and which also shows that a four-state HMM fits the data best.

As we report in **Table 4.7**, we identify 4 states for the service providers' CX performance from the dataset. The four states differ substantially in terms of the rating score received from their customers. For ease of discussion, we refer to the four CX performance states as low, medium, high, and very high, denoted as L, M, H, and H+, with corresponding CX performance scores of 5.63, 7.23, 8.36, and 9.21. The initial probabilities of being in the L, M, H, and H^+ performance states are 0.09, 0.31, 0.32, and 0.27, respectively. In addition, in the migration path probability matrix, the diagonal represents the mean probability of remaining in the same CX performance state (i.e., stickiness) and the off-diagonal values indicate the probability that a firm in a given state will migrate to a different performance state. To assess whether these migrations are random or influenced by the migration mechanisms, we test another HMM without variable specifications in the transition matrix, and it provides a worse fit. Therefore, the set of value co-creation strategies can explain CX performance migrations. This confirms the importance of conducting research that uses customers' aggregated perceptions and evaluations, since this can generate strategies for energizing firm CX performance or preventing its deterioration.

Table 4.7 Results: HMM of CX Performance States

Firms' CX Performance States				
	Low (L)	Medium (M)	High (H)	Very High (H^+)
Size	6.4%	19.9%	40.6%	33.1%
Rating Score	5.80	7.32	8.32	9.23
Initial State Probability of Each State				
	Low (L)	Medium (M)	High (H)	Very High (H+)
	0.11	0.28	0.33	0.28
Transitional Probability between States				
	To Next State			
Move from Previous State	**Low (L)**	**Medium (M)**	**High (H)**	**Very High (H+)**
L	**0.46**	0.02	0.29	0.23
M	0.11	**0.74**	0.03	0.11
H	0.13	0.18	**0.46**	0.23
H+	0.06	0.02	0.21	**0.71**

Note: the values in the transition matrices shown in bold indicate the most likely destination for firm CX performance in a specific current state at a given time point.

The L state is characterized by lower levels of CX performance, expressed by the 5.80 average rating score. This lower performance state also exhibits "positive future movement". Firms in the L state move to a stronger state 54% of the time and remain in the same state 46% of the time. The M state exhibits a moderate level of CX performance, represented by the average rating score of 7.32. It is the stickiest state with 74% remaining in this state each period, while 14% of firms move up and 11% of firms show a downward movement. The H state exhibits the CX performance of firms that have an average rating score of 8.32. Firms in the H state move to a higher performance state

23% of the time and a lower performance state 31% of the time; they remain in the H performance state 46% of the time. The H+ state is the highest level of CX performance, represented by an average rating score of 9.23. In terms of migration, it is relatively sticky (71% remain each period). However, this means that firms in the H+ state have a 29% probability of dropping to a lower performance state. Our finding reinforces the importance of having migration mechanisms to motivate firms to move from a lower CX performance state to a higher state or to prevent their deterioration from a higher performance state to a weaker state.

Table 4.8 State Dependent Effects of Four Dimensions of Perceived CX on Firms' CX Performances

Covariates	Low State (L) Coef.	Low State (L) Z value	Medium State (M) Coef.	Medium State (M) Z value	High State (H) Coef.	High State (H) Z value	Very High State (H+) Coef.	Very High State (H+) Z value
Affective CX	**-0.29*** **	**-11.64**	**-0.09*** **	**-6.74**	**0.12*** **	**12.18**	**0.27*** **	**27.89**
Cognitive CX	0.01	0.52	**0.02** **	**2.12**	**-0.01* **	**-1.94**	**-0.01** **	**-2.05**
Social CX	-0.01	-0.84	**-0.03*** **	**-3.74**	-0.00	-0.68	**0.04*** **	**7.82**
Physical CX	0.00	0.04	0.01	0.77	0.01	0.96	**-0.02** **	**-2.01**

Note: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

We then examine the state-dependent effects of perceived CXs on the rating score and set forth the results in **Table 4.8**. In our research framework, which depicts the trajectory of firm CX performance, we hypothesize that the guests' perceived multidimensions of CXs will exert short-term effects (namely, state-dependent effects) on the rating scores, determining the "current state" of the firm's CX performance. Our rationale is that the covariates (the four dimensions of CX perceptions in the current study) included in the state-dependent distribution will, by definition, affect firm behaviors only in the current time period. They are conditional on the firm's current state and therefore have a short-term effect. We argue that the rating score given by the guests is also determined by their perceived CXs regarding their hotel stay experiences. In **Table 4.8,** the coefficients of the affective-emotional dimension of CX are -0.29, -0.01, 0.12, and 0.27 (all significant at 1%) for states L, M, H, and H+, respectively. The results indicate that affective CX has a positive relationship with the higher level CX performance states (the H+ and H states) but that as the firm drops to the lower performance states, the affective CX perception transforms from a positive factor to a negative one. In other words, a lower level of affective CX determines the lower level of the CX performance state (the L and M states); a higher level of affective CX shapes the higher level of the CX performance states (the H and H+ states). Additionally, the increasing magnitude of the coefficients for the H+ and L states show that consumers' perception of affective CX plays a critical role as firms move toward the extremities of their performance states (H+ or L).

For other dimensions of CX perceptions, we find a negative relationship between cognitive CX and a higher CX performance state but a positive relationship between cognitive CX perception and a medium performance state. The negative coefficients in state H (-0.01, significant at 10%) and H+ (-0.01, significant at 5%) suggest that the higher the firms' CX performance, the lower the cognitive dimension of CX perception. Moreover, cognitive CX exerts relatively essential influences on the M state, in comparison to the other three states.

Regarding the social dimension of CX perception, the coefficient is positive and significant in the H+ state (0.04, significant at 1%) but negative in the M state (-0.03, significant at 1%). This indicates that when a firm has a higher level of CX performance, its customers' perceived social CX is positive (i.e., happy family time in the focal hotel). However, as a firm's CX performance transitions from state H+ to state M, the perceived social CX is no longer a positive experience but a negative one (e.g., being disturbed by a noisy family or a baby crying at midnight).

In general, we find that firms with the highest level of CX performance (H+ state) have positive relationships with customers' affective and social CXs but negative relationships with customers' cognitive and physical CXs. That is, affective and social CXs are the first two important dimensions to determine firm's highest performance state (H+).

Firms in the H state have positive relationships with customers' affective CX perceptions but negative relationships with customers' cognitive CX perceptions. In short, the affective dimension of CX is the most important factor for determining that a firm's current performance is in the H state. Firms in the M performance state have negative relationships with their customers' affective and social dimensions of CX perceptions but positive relationships with customers' cognitive CX perceptions; this contrasts with firms in the H+ performance state. In other words, relatedly lower levels of affective CX and social CX are the most influential dimensions for shaping a firm's current performance in the M state. Finally, firms in the L state have a negative relationship with customers' affective CX perceptions, such that the lowest level of affective CX is the most critical factor for determining a firm's performance as being in the lowest L state.

We conclude that there are opposite patterns between H+ state and L state. That is, H+ state is positively determined by affective CX and social CX but negatively determined by cognitive CX and physical CX. L state is also positively determined by the affective CX and social CX dimensions but, in contrast to the H+ state, it is also positively determined by the cognitive CX and physical CX dimensions. In a word, affective CX exerts the most influential short-term impact determining the highest and lowest levels of firms' CX performance states.

4.4.2.2 The Migration Effects of Positive Mechanisms

Table 4.9 presents the parameter estimates of the positive value co-creation mechanisms (the variables concerned with the ARCI elements extracted from guests' positive comments) across six upgrade migration paths. This allows us to highlight the most effective strategies for upward migration. The first positive value co-creation element related to firm activities significantly increases the probability of firms moving from a lower performance state (L) to a higher state (M, H, H+). The second element of the positive ARCI mechanism is customers' activities, which is less effective at triggering upward migration. Interestingly, for the third and fourth elements of the positive mechanisms, firms' and customers' resources both exert backfire effects on the upward migration paths. Positive perceptions of firms' resources reduce the likelihood of firms transitioning from the M to the H+ performance state (-0.09, significant at 1%) and from the H to the H+ state (-0.08, significant at 1%). Positively perceived customers' resources decrease the likelihood of a transition from the H to the H+ state (-0.58, significant at 5%). As for the fifth element of the positive ARCI mechanism, contexts that are perceived to be positive have significant impacts on shifting a firm's performance from the M to the H state (0.05, significant at 4%), from the M to the H+ state (0.15, significant at 1%) and from the H to the H+ state (0.05, significant at 5%). The final element (positive interaction between firm and customer) significantly increases the probability of an upward transition from the L state to the M state (0.24, significant at 1%), from the L state to the H state (0.18, significant at 10%), from the M state to the H state (0.08, significant at 5%), and from the H state to the H+ state (0.07, significant at 10%).

Table 4.9 The Effectiveness of the Positive Migration Mechanisms

The Effects of the Positive Value Co-Creation Mechanism on Upward Paths						
Positive ARCI Elements	**L →M**	**L→H**	**L→H+**	**M→H**	**M→H+**	**H→H+**
Firms' Activities	**0.23*****	**0.21****	**0.34****	**0.10*****	0.04	-0.00
	(3.17)	**(2.01)**	**(2.02)**	**(3.14)**	(0.71)	(-0.03)
Customers' Activities	0.01	0.00	-0.05	0.05	**0.10***	0.08
	(0.08)	(0.01)	(-0.15)	(0.94)	**(1.74)**	(1.29)
Firms' Resources	0.02	-0.00	-0.02	0.00	**-0.09*****	**-0.08*****
	(1.35)	(-0.12)	(-0.36)	(0.15)	**(-3.59)**	**(-4.30)**
Customers' Resources	0.14	0.05	-6.99	-0.02	0.00	**-0.58****
	(1.38)	(0.29)	(-0.20)	(-0.39)	(0.07)	**(-2.40)**
Positive Contexts	-0.04	0.06	0.06	**0.05****	**0.15*****	**0.05****
	(-0.82)	(1.15)	(0.58)	**(2.26)**	**(5.51)**	**(2.27)**
Positive Firm-Customer Interaction	**0.24*****	**0.18***	0.15	**0.08****	0.07	**0.07***
	(3.03)	**(1.71)**	(0.98)	**(2.15)**	(1.06)	**(1.67)**

The Effects of Seven Specific Positive Criteria on Upward Migration Paths						
Criteria Existing on Booking.Com	**L→M**	**L→H**	**L→H+**	**M→H**	**M→H+**	**H→H+**
Positive_Staff	-0.00	-0.01	0.01	**0.14*****	0.04	-0.01
	(-0.04)	(-0.06)	(0.05)	**(5.89)**	(0.85)	(-0.12)
Positive_Facilities	**0.13*****	-0.07	**0.15*****	**0.07*****	**0.06****	-0.03
	(2.81)	(-0.60)	**(2.99)**	**(2.51)**	**(2.40)**	(-0.91)
Positive_Location	0.01	-0.01	-0.04	0.00	**-0.10*****	-0.02
	(0.96)	(-0.21)	(-0.64)	(0.28)	**(-3.77)**	(-1.04)
Positive_Free WiFi	-0.71	0.09	-12.82	-0.03	-30.59	-3.36
	(-0.38)	(0.21)	(-0.01)	(-0.10)	(-0.05)	(-0.48)
Positive_Cleanliness	0.16	0.20	0.13	-0.04	-0.04	-0.83
	(1.87)	(1.61)	(0.88)	(-0.67)	(-0.46)	(-1.38)

Positive_Comfort	-2.99	1.78	-1.91	0.35	**0.60*** **	0.11
	(-0.04)	(1.05)	(-0.02)	(1.24)	**(2.77)**	(0.35)
Positive_Value for Money	0.07	-0.40	-7.25	-0.53	0.06	-2.73
	(0.52)	(-0.51)	(-0.07)	(-1.48)	(0.69)	(-0.93)

Note 1: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
Note 2: the numbers in brackets are the Z-values of the parameter estimates.

We now turn to the effects of the seven experience evaluation criteria used by Booking.com on the upward transition probabilities (bottom panel in **Table 4.6**). For hotels moving from L to M and from L to H+ performance states, guests' positive perceptions of the focal hotel's facilities are the most effective upward mechanisms (0.13 and 0.15, respectively, both significant at 1%). For hotels moving from the M state to the H state, guests' positive perceptions regarding the hotel staff and facilities are both productive. For hotels moving from the M state to the H+ state, positive perceptions of both the facilities (0.06, significant at 5%) and comfort (0.60, significant at 1%) can promote upward migration. However, guests' positive perceptions of the hotel location exert the opposite effect, being detrimental to upgrading hotels' CX performance (-0.10, significant at 1%). For hotels moving from the H to the H+ state or from the L state to the H state, the seven Booking.com criteria have no significant impact.

In general, the positive mechanisms that most effectively promote upward migration are firms' activities and positive interactions between experience providers and receivers. These two positive mechanisms can effectually boost firms' CX performance, propelling them out of the lowest L state into the higher states. On the other hand, when we look at Booking.com's seven evaluation criteria, perceived facilities is the one that will most significantly influence 4 out of the 6 upward migration paths. We thus conclude that, from the theoretical lens of the ARCI value co-creation mechanism, firms' activities, positive contexts and positive interactions are the most crucial components for increasing the likelihood of firms' upward movement. This finding is consistent with Gronroos (2012)'s conceptualization of companies as ‘‘value facilitators’’ as well as responding to McColl-Kennedy et al. (2019)'s findings that company's activities receive the greatest attention in customers' verbatim reviews. Interestingly, firms' resources exert backfire effects on the paths from the lower states to the highest state (H+). We thus conclude that to propel a firm's CX performance toward the highest H+ state, it is not recommended that it invest in physical resources. Firms should pay attention to how they perform/deliver service, cultivating positive contexts to trigger superior interactions with customers.

From a Booking.com hotel's perspective, its guests' perceptions of its facilities must be the first managerial consideration if action is to be taken to increase the probability of boosting guests' evaluations and rating scores. Furthermore, the quality of the staff is important to move CX performance from M to H state while the quality of the hotel's comfort is crucial to moving the firm's performance from N to H+ state.

Finally, **Figure 4.5** depicts the different impacts exerted by the ARCI components on six upward migration paths. To conclude, firms' activities and the interactions between experience providers and receivers are the two most essential components for enabling upward migrations. In terms of the seven criteria on Booking.com, the quality of the hotel's facilities is the most important factor for improving its CX performance from the lower to higher states.

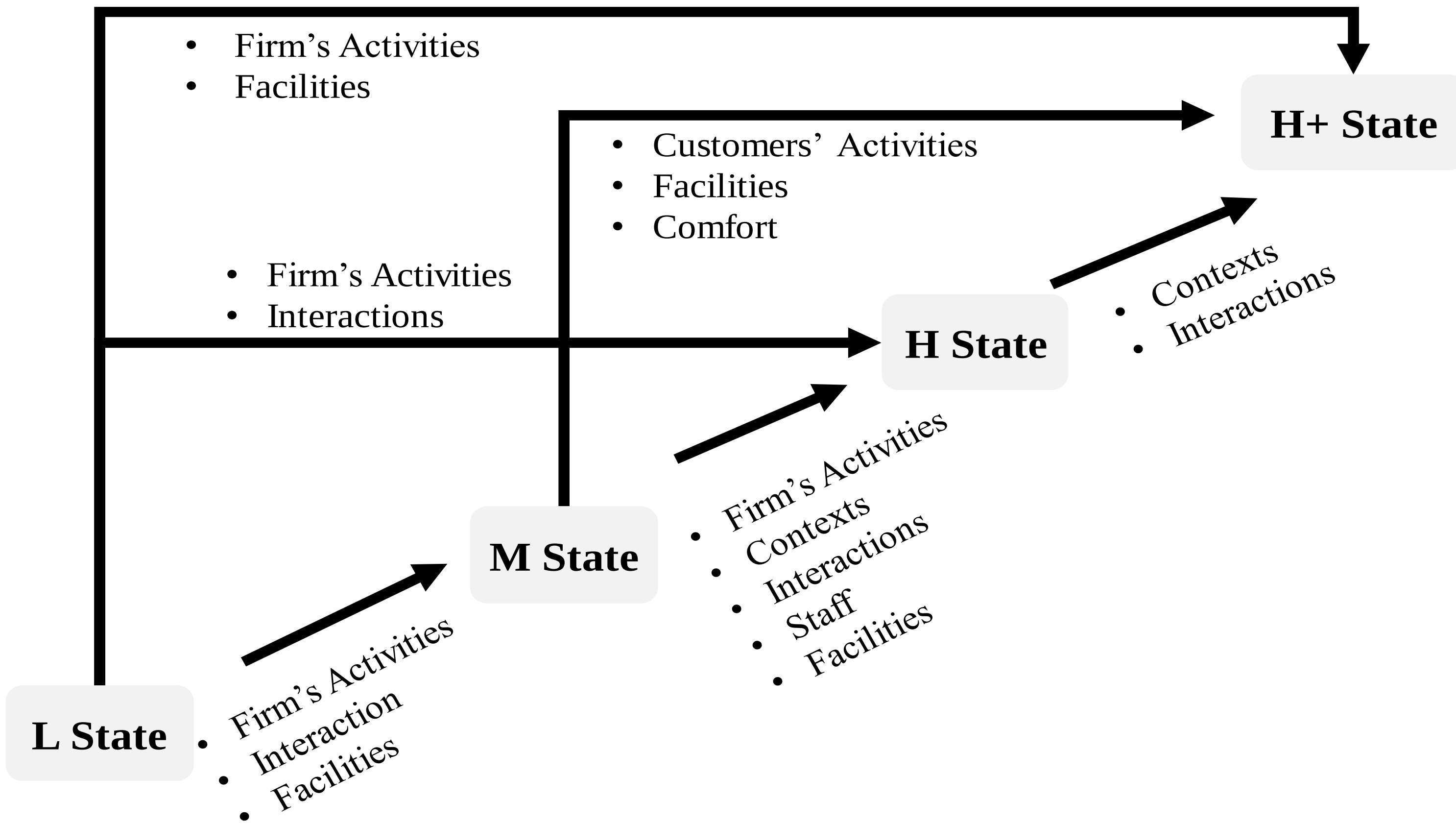


Figure 4.5 The Effectiveness of Positive Migration Mechanism on Upward Migration Paths

Table 4.10 Scenario Analysis: The Marginal Effects of the Significant Positive ARCI Components and Evaluation Criteria on Booking.Com

		CX Performance State			
		L State	**M State**	**H State**	**H+ State**
(a)		**Baseline Transitional Probabilities**			
	From	**To**			
Original transition probability matrices, without firms' strategic inputs	L	0.46	0.02	0.29	0.23
	M	0.11	0.74	0.03	0.11
	H	0.13	0.18	0.46	0.23
	H+	0.06	0.02	0.21	0.71
ARCI Components		**The Changing Transitional Probabilities of Scenario 1**			
(b) Scenario 1	**From**	**To**			
Increasing one unit of firm's activities, positive context, and positive interaction	L	0.02	0.31	0.19	0.48
	M	0.08	0.31	0.35	0.27
	H	0.00	0.05	0.59	0.36
	H+	0.00	0.00	0.13	0.87
Booking.com Criteria		**The Changing Transitional Probabilities of Scenario 2**			
(b) Scenario 2	**From**	**To**			
Increasing one unit of positive staff, positive facilities, and comfort perceptions	L	0.02	0.00	0.98	0.00
	M	0.00	0.32	0.24	0.44
	H	0.00	0.00	0.87	0.13
	H+	0.00	0.03	0.00	0.97

Moreover, to quantify the marginal effects of the positive mechanism on the probability of transitioning, we calculate the transitional probabilities when the mean value of the focal variables (the significantly effective variables from the ARCI mechanism and the Booking.com evaluation criteria) are increased by one unit while holding the other non-significant variables constant. Matrix (b) in **Table 4.7** shows the transition probabilities caused by such changes in the positive perceptions of the firm's activities, combining the perceived positive contexts and perceived positive interactions. We focus on the integration of these three effective elements found in **Table 4.9** to identify the optimal strategic allocation for achieving the best CX performance results. Following the same rationale, matrix (c) in **Table 4.10** shows the transition probabilities caused by one-unit changes in the integration of positive staff perception, positive facilities perception, and positive comfort perception; these being three effective variables taken from the experience evaluation criteria listed on the Booking.com website. We choose these variables not only because they are statistically significant but also because they are the mechanisms that the service providers (i.e., the hotels' managers) can control. We then compare the differences between respective cells of the original matrix (a) and the other two matrices (b) and (c) to quantify the marginal effect on the transition probability. For example, the matrix (b), representing the strategic allocation of increasing positive activities, positive contexts, and positive interactions, hypothetically increases the probabilities of transitioning from the lower performance states to the higher performance states. We find that increasing one unit of firms' activities, positive context and positive interactions will improve the upward migration probabilities from L to M state and from L to H+ state. The original probabilities of these two paths are 0.02 and 0.23; the altered probabilities of these two paths in scenario 1 are 0.31 and 0.48. This scenario also increases the upward probabilities from M to H state and from M to H+ state. We find that the original probabilities of these two paths are 0.03 and 0.11; their altered probabilities in scenario 1 are 0.35 and 0.27. Moreover, this strategy raises the probability of going from H state to H+ state (from the original probability of 0.23 to the new probability of 0.36) and increases the probability of retaining customers in the highest state from 0.71 to 0.81.

Two points are worth noting regarding matrix (c). First, these strategic investments are effective at decreasing the likelihood of moving from the higher states (M, H, H+) down to L state and they also decrease the probability of remaining in the lower performance state. Furthermore, while we find that increasing one unit of positive staff, positive facilities, and comfort will increase the likelihood of going from L to H state (0.29 → 0.98), this will decrease the probabilities of going from L to the preferred H+ state (0.23→0.00). We thus contend that this strategy is not recommended for firms who seek to tweak their performance so that they leave the L state. This scenario also increases the upward probabilities of going from M to H state and from M to H+ state. We find that the original probabilities of these two paths are 0.03 and 0.11; the altered probabilities of these two paths in scenario 2 are 0.24 and 0.44. This scenario also increases the retention probability in the highest H+ state from 0.71 to 0.97. However, it is not beneficial for companies that are aiming to migrate their performance from H to H+ state.

The second consideration of scenario 2 concerns its effectiveness as a positive mechanism to improve the firm's CX performance. We argue that of the measures that are effective for moving hotels from the lower performance states (L, M, H) to the highest one (H+), the combination of single-unit changes in staff, facilities, and comfort perceptions exerts fewer effects compared to the strategic combination of changes in positive contexts, interactions, and hotel activities.

4.4.2.3 The Migration Effects of the Negative Mechanisms

Table 4.11 presents the parameter estimates of all of the negative migration strategies across the six downward migration paths. This allows us to highlight the most influential negative elements for these six paths.

Table 4.11 The Effectiveness of the Negative Migration Mechanisms

			The Effects of Negative Mechanism on Downward Paths			
Negative ARCI Elements	H^+→H	H^+→M	H^+→L	H→M	H→L	M→L
Firms' Activities	**0.12*****	0.07	0.10	0.06	**0.11****	-0.10
	(2.96)	(0.63)	(0.53)	(0.94)	**(2.15)**	(-0.73)
Customers' Activities	**0.10*****	0.01	0.05	0.01	-0.16	0.08
	(3.07)	(0.09)	(0.51)	(0.13)	(-0.96)	(1.06)
Firms' Resources	-0.00	**0.06*****	**0.06*****	-0.03	-0.11	-0.00
	(-0.12)	**(3.40)**	**(2.49)**	(-1.31)	(-1.49)	(-0.12)
Customers' Resources	**0.08*****	0.04	-0.11	-0.00	0.03	0.11
	(2.97)	(0.61)	(-0.29)	(-0.03)	(0.35)	(1.04)
Negative Contexts	**0.06****	0.02	0.00	-0.02	0.03	-0.09
	(2.33)	(0.49)	(0.00)	(-0.58)	(0.25)	(-0.90)
Negative Firm-Customer Interaction	**0.53*****	0.32	**0.50****	-0.53	**0.45****	**0.38****
	(3.34)	(1.06)	**(1.93)**	(-1.19)	**(2.44)**	**(1.97)**
			The Effects of 7 Specific Negative Experience Criteria on Downward Migration Paths			
7 Criteria from Booking.com	H^+→H	H^+→M	H^+→L	H→M	H→L	M→L
Negative_Staff	-1.48	0.12	**0.31***	-39.88	-0.41	0.06
	(-0.58)	(0.34)	**(1.78)**	(-0.08)	(-0.36)	(0.33)
Negative_Facilities	**0.05****	**0.07*****	**0.07****	**-0.10*****	-0.07	-0.01
	(2.22)	**(3.20)**	**(2.15)**	**(-2.50)**	(-1.01)	(-0.16)
Negative_Location	-0.16	0.01	-0.00	-0.11	0.03	0.07
	(-0.74)	(0.12)	(-0.02)	(-0.57)	(0.33)	(0.61)
Negative_Free WiFi	0.06	-0.00	-9.82	-0.08	-15.45	-0.14
	(0.52)	(-0.03)	(-0.03)	(-0.56)	(-0.02)	(-0.34)
Negative_Cleanliness	-0.46	-0.71	-7.87	-0.15	-0.46	-0.04
	(-0.25)	(-0.55)	(-0.05)	(-0.31)	(-0.25)	(-0.14)
Negative_Comfort	**0.55*****	**0.40****	**0.51****	0.06	0.12	0.09

	(3.90)	**(2.18)**	**(2.18)**	(0.57)	(0.90)	(0.41)
Negative_Value for Money	**0.10*** **	-0.09	-0.17	0.01	-0.07	-0.01
	(3.91)	(-0.70)	(-0.28)	(0.35)	(-0.27)	(-0.07)

Note 1: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level
Note 2: the numbers in brackets are the Z values of the parameter estimates

The first negative migration element is customers' negative perceptions of firms' activities, which has the significant impact of shifting a hotel's CX performance from the H+ state to the H state (0.12, significant at 5%) and from the H state to the L state (0.11, significant at 5%). The second element is negative perceptions of customers' activities. This increases the likelihood of moving downward from the H+ state to the H state (0.10, significant at 1%). The third and fourth elements, negative perceptions of firms' resources and customers' resources, are both detrimental to maintaining the higher performance states. The former affects firms' downward migration from the H+ state to the M state and from the H+ state to the L state (both are 0.06, significant at 1%); the latter increases the likelihood of a detrimental transition from the H+ state to the H state (0.08, significant at 1%). The fifth element of the negative mechanism, perceived negative contexts, exerts deteriorating effects that shift a firm's CX performance state from the H+ state to the M state (0.06, significant at 5%). Finally, the perceived negative interactions between firms and customers significantly worsen firms' performance from the higher to the lower states. Regarding the seven experience criteria variables available on Booking.com, we find that four of these (guests' negative perceptions of hotel facilities, staff, comfort, and value for money) significantly increase the likelihood of a downward transition from higher to lower CX performance states.

From the theorical perspective of the ARCI value co-creation mechanism, it can be seen that the component of negative interactions between experience providers and receivers is the most powerful trigger for downward migrations from the higher states to lower states. Specifically, the two most-commonly deteriorating paths (from H+ to L, and from H to L) indicate that managers should pay attention not only to their interactions with guests but also to their firms' resources (for the former path) and firms' activities (for the latter path) to prevent a deterioration in their CX performances. Examining the matter through the real-world lens of Booking.com, guests' negative evaluations/perceptions of hotels' staff, facilities, and room comfort are the top three causes of a drop in the rating scores from the highest level to the lowest (H+ state →L state).

Figure 4.6 depicts the different effects exerted by different negative components on six downward paths. In short, firms' resources and activities as well as negative interactions between experience providers and receivers are the most significant components for triggering the downward migrations of firms' CX performance. Regarding the seven evaluation criteria on Booking.com, the results show that facilities and comfort are the most two criteria that most strongly impact downward migration.

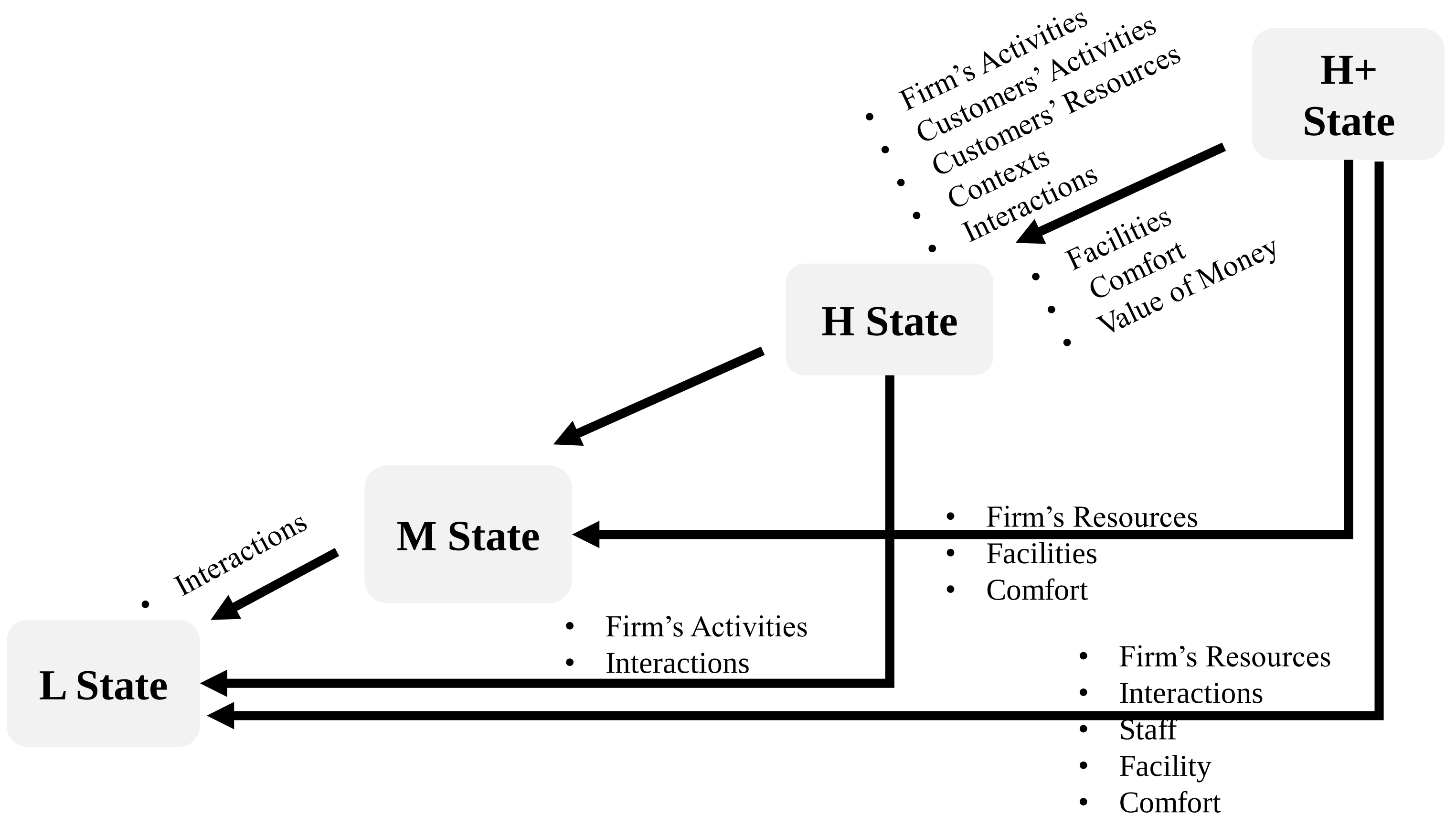


Figure 4.6 The Significant Negative Mechanisms on CX Performance of Downward Migrations

To quantify the marginal effects of the significant negative variables found in **Table 4.11**, we run two scenarios that feature a one-unit increase from the mean values of the focal variables. We calculate the transition probabilities when the mean values of the significant negative variables found in **Table 4.11** are increased by one unit, while holding constant all the positive mechanisms and the other nonsignificant negative mechanisms. The first scenario shows the deteriorating changes in the probabilities caused by increasing the negative perceptions of hotels' activities and resources, and negative interactions between hotels and guests. The second scenario shows the effects caused by increasing the negative perceptions of hotels' staff and facilities, and negative feelings about hotel comfort. We choose these variables not only because they are statistically significant variables in **Table 4.11** but also because they are manageable and controllable by the firms.

In **Table 4.12**, the first negative scenario increases the probabilities of a downward transition from a higher state to a lower state. We find that increasing by one unit the negative firm's activities, negative firm's resources, negative contexts, and negative interactions increases the probabilities of dropping from the H+ state to the H, M, and L states. The original probabilities of these three paths in scenario 1 are 0.21, 0.02, and 0.06; the new probabilities of these three paths are 0.46, 0.05, and 0.09 respectively. The negative combinations also deteriorate the downward likelihoods from H to M state and from H to L state. The original probabilities of these two paths in negative scenario 1 are 0.18 and 0.13; the altered probabilities of these two paths are 0.21 and 0.25. Moreover, this negative combination further increases the downward likelihood from M to L state (0.11→0.26) and increases the probability of remaining in the lowest L state

(0.46→0.93).

Similar patterns are found in the results for the second scenario. That is, a one-unit increase in the negative perceptions of hotel's staff and facilities and the room's comfort will not only increase the probabilities of deteriorating from the higher states to the lower state but will also increase the likelihood of staying in the lowest state. We find that increasing by one unit the negative perceptions of hotel staff, facilities, and comfort increases the downward probabilities from H+ state to the H, M, and L states. The original probabilities of these three paths in scenario 2 are 0.21, 0.02, and 0.06; the changing probabilities of these three paths in negative scenario 2 are 0.42, 0.04, and 0.13 respectively. The negative combinations in scenario 2 also deteriorate the downward likelihoods from H to L state (the original probability is 0.13; the new one is 0.20). Moreover, this negative combination further increases the downward likelihood from M to L state (the original probability is 0.11; the new probability is 0.34) and increases the retention probability in the lowest L state from 0.46 to 0.97.

Table 4.12 The Marginal Effects of Significant Negative Mechanisms

		CX Performance State			
		L State	**M State**	**H State**	**H+ State**
		The Baseline of Transitional Probabilities Matrix			
	From	To Next State			
Original matrix without any change in negative mechanisms	L	0.46	0.02	0.29	0.23
	M	0.11	0.74	0.03	0.11
	H	0.13	0.18	0.46	0.23
	H+	0.06	0.02	0.21	0.71
Negative Scenario 1 : ARCI Component		**Changing Transitional Probabilities of Negative Scenario 1**			
	From	**To**			
Increasing by one unit the negative firm's activities, firm's resources, contexts, and interactions	L	0.93	0.07	0.00	0.00
	M	0.26	0.74	0.00	0.00
	H	0.25	0.21	0.54	0.00
	H+	0.09	0.05	0.46	0.41
Negative Scenario 2: Booking.Com Criteria		**Changing Transitional Probabilities of Negative Scenario 2**			
	From	**To**			
Increasing by one unit the negative perceptions of hotel staff, facilities, and room comfort	L	0.97	0.03	0.00	0.00
	M	0.34	0.66	0.00	0.00
	H	0.20	0.16	0.64	0.00
	H+	0.13	0.04	0.42	0.41

4.5 Discussion and Conclusion

Using longitudinal textual data collected from Booking.com, we conduct a series of text mining procedures that includes preprocessing the data, developing custom dictionaries, assessing the validity of the dictionaries, converting texts into quantifiable measures, and aggregating the individual datasets into a firm-level dataset. Our final panel dataset consists of 1,019 hotels with their corresponding numeric variables for 13 single week time-periods. Using an HMM, we capture the trajectory of firms' CX performance using the rating scores given by their customers and associate the CX performance with four dimensions of CX as perceived by the customers (affective, cognitive, social, and physical CX perceptions). We also capture firms' migration among the different states of CX performance through positive and negative migration variables extracted from the guests' positive and negative comments.

4.5.1 Theoretical Contribution

We identify four CX performance states ranging from low to high levels, denoted as L, M, H and H+ states, which represent real rating scores of 5.80, 7.32, 8.32, and 9.23 respectively. The performance states are associated with four theory-rich state variables comprising the following CX dimensions: affective CX; cognitive CX; social CX; and physical CX. We find that the affective dimension of CX is positively associated with the highest performance state and negatively associated with the lowest performance state. In other words, in the short-term, affective CX exerts the strongest effect determining firms' CX performance states (limited to the current state). We use the lens of value co-creation to propose (positive and negative) ARCI migration mechanisms that influence change in firms' CX performance. Each positive and negative component in the ARCI mechanism influences the CX performance states at different times in different patterns and reflects the potential development and decline of a firm's CX performance.

We find that (1) interaction is the most important component in both the positive and negative mechanisms, (2) firm's activities is a positive mechanism that plays a role in boosting performance from L to H+ state, and (3) firm's resources is a negative mechanism that throws firms' CX performances into a steep decline, from H+ state to L state. Therefore, we conclude that if managers are to actively promote their firms' CX performances, they should focus on their major activities/actions that will increase their customers' affective dimension of CX. On the other hand, to prevent a decline in CX performance, managers should focus on guests' negative perceptions of firms' resources. In other words, firms' activities can be seen as an active CXM tool for boosting performance and maintaining quality. Investing in firms' resources can be viewed as a passive tool for preventing a deterioration in performance.

This study advances the literature in several ways. First, we contribute to the CX and CXM literature by applying a dynamic lens through which to view CX from the perspective of service providers. We propose a research framework, namely, the trajectory of firm CX performance. With this, we aim to study the short-term effects (state-dependent effects) of CX perceptions and the long-term effects (migration effects) of the value co-creation mechanisms on firm CX performance dynamics. We identify four CX performance states that increase the rating score given by customers and we identify the dynamic effects of the different migration variables on firms' transitions among the four performance states. Drawing on the theoretical perspective of value co-creation, we design a double-faceted

ARCI mechanism that incorporates the ARCI elements of activities (A), resources (R), contexts (C), and interactions (I) in both positive and negative terms, thereby parsimoniously accounting for changes in firm CX performance. Moreover, we identify effective, state-specific CX management strategies. We find, for example, that improving firm “activities” (A) is more effective at promoting firm performance from the lowest state to a moderate state, while establishing positive “contexts” (C) is more effective at raising firm performance from a moderate to a higher level. We also note the backfire effects exerted by positive perceptions of firms’/customers’ “resources” (R) on the upward migration paths from the M/H state to the H+ state. This means that the more resource perceptions there are, the lower will be the likelihood of a firm transitioning from the M to the H+ performance state. We find that to move firms from a moderate state (M) to a higher performance level, the most effective strategic variables are customers’ activities, positive contexts, and positive interactions. This is because the strategic allocation must match firms’ CX performance state.

Moreover, previous CX and CXM scholars have called for future research to focus more strongly on the trajectories of CXM and investigate the dynamic nature of this concept along with its identified contingency factors (Homburg et al., 2017, Lemon & Verhoef, 2016). To respond to these calls, we propose the framework of a firm’s CX performance trajectory, examining it from a dynamic perspective. This study not only examines the dynamic effectiveness of different CX management variables throughout the CX performance trajectory but also expands the perspective of the migration mechanism from single-faceted to double-faceted. The positive and negative migration mechanisms influence firms’ CX performance at different times and in different patterns, reflecting the potential improvement or decline in firm performance. We advance the CX/CXM theory with a detailed understanding of the dynamics of firm CX performance, performance state migration, and the most effective strategic synergies for each transition path. Specifically, customers' CX perceptions (the perceived affective, cognitive, social, and physical CX) exert short-term effects that pertain to different levels of firm CX performance; for example, the affective and social dimensions are more closely related to the higher states, while cognitive perceptions are more related to the lower performance states. The long-term effects of the positive/negative migration mechanisms highlight an emerging CXM theory that is informed by four tenets. According to the first tenet, positive perceptions of firms' activities and positive interactions between firms and customers are effective at improving firms' CX performance and thereby effect a transition from the lower (L) level. Tenet 2 holds that positive contexts and interactions and positive perceptions of both firms' and customer activities are effective at improving firm CX performance from a moderate level to the higher states. Tenet 3 states that negative mechanisms exert a more damaging impact on firms in the highest state (H+) than on those in a moderate state (M/H). Tenet 4 holds that negative perceived interactions have relatively strong adverse effects on firm performance.

Second, this study contributes to the service research literature on value co-creation. Drawing on McColl-Kennedy (2019; 2012), Macdonald et al. (2016), and Ordenes et al. (2014), this study integrates their value co-creation perspective for managing CX performance dynamics. We leverage their work regarding the value creation elements and text mining techniques to measure CX, with the aim of extending their contributions and gaining insights into CX dynamics by adopting an HMM perspective. This dynamic perspective is a unique feature since the existing service science research relies on the conventional static approach. As such, we extend the value creation literature by synthesizing, extending, and adding a dynamic perspective that comprehensively illustrates how to manage a service provider's CX performance from the customers' perspective. Consistent with this customer-centered perspective, our research further references previous contributors to highlight the value of a consumer-based strategy for generating insights and developing an organizational strategy (Bettencourt et al., 2014; Hamilton, 2016; Hamilton & Price, 2019; Rawson et al., 2013; Seybold 2001). In addition to adding a customer-focused and dynamic perspective to the value co-creation literature, we further enrich this research stream by applying seven experience evaluation criteria drawn from the Booking.com website to the ARCI framework. The four criteria of staff, facilities, location, and free Wi-Fi are topologized as the firm's resources. The two criteria of cleanliness and comfort are categorized as the firm's activities. The last criterion of value for money is classified under customers' resources. We empirically show how guest reviews on Booking.com enable us to realize the value co-creation conceptualization in an important real-world setting: hotel stay experiences in the service industry. Our creation of this dynamic model sheds light on a key practical question: how to design effective CX management strategies for the hotels listed on Booking.com. From our empirical settings, we argue that the extended value co-creation perspective and our ARCI mechanism are transferable and that such transferability is critical to producing new knowledge that can advance the service research literature.

Third, we contribute to the HMM literature. To our knowledge, no prior HMM study has conducted research on CX dynamics or CX performance dynamics. This is the first study to examine the evolution of firm CX performance using longitudinal, unstructured text datapoints at the individual level (guest reviewers' verbatim comments and rating scores). By adopting the data aggregation technique, we leverage the detailed and rich consumer insights from individual datasets, analyze them at the firm level, and interpret them to design firms' CX management strategies. We also advance the HMM literature in other methodological ways. We demonstrate the usefulness of a text mining procedure that transforms qualitative data into quantitative data, thereby addressing the call from many marketing scholars (Berger et al., 2019; Balducci & Marinova, 2018; Marketing Science Institute, 2014; 2016) to develop and validate a novel CX analytic that can make sense of unstructured big data.

4.5.2 Managerial Implications

We provide step-by-step guidelines for practitioners to demonstrate how our analytical approach can help them to disentangle the complexities of textual data and identify latent states from unstructured text data. More importantly, we identify where resources should be focused to adapt and potentially redesign the CX, emphasizing what really matters to customers and which actions managers should take. The deep insights gained from our approach should produce a fuller understanding of the complexity of firm CX performance trajectories and the ways in which CX performance might be enhanced.

Whenever possible, managers should consider multiple facets of their CX performance and their guests' experience encounters. The different patterns of all four CX performance states determine CX performance conceptualizations that are unique.

Managers must realize that developing CX management strategies without examining the underlying mechanism in detail can lead to inefficient resource allocation.

In **Table 4.13,** we offer a summary of our research findings that will enable managers to identify their current CX performance states and deploy the relevant migration strategies based on these states. Moreover, three major takeaways emerge from our empirical results listed as follows:

(1) The state-dependent effects (short-term effects) exerted by four dimensions of CX perceptions: Affective dimension of CX is the most critical factor for determining the firm's current state of CX performance. A lower level of affective CX will shape lower CX performance, presented as a lower rating score; a higher level of affective CX will determine a higher performance state in the current period, presented as a higher rating score.

(2) The migration effects (long-term effects) exerted by the positive mechanism: Increasing firm's activities to cultivate positive contexts and encourage positive interactions are effective strategies to boost upward migrations. Specifically, improving customers' positive perceptions of the firm's activities is the strategy most likely to propel the firm's CX performance out of the L state.

(3) ***The migration effects (long-term effects) exerted by the negative mechanism:*** Increasing the negative perceptions of the firms' activities and resources, and the service contexts and interactions, will together deteriorate firms' CX performance from the higher states to the L state, partially offsetting the benefits generated by the positive mechanism. Moreover, customers' negative perceptions of hotel staff, facilities, and comfort on Booking.com will deteriorate hotels' CX performances.

Managers must be aware that the evaluation criteria on Booking.com are more influential as a negative mechanism that injures performance than as a positive mechanism for improving it.

Table 4.13 Managerial Implications Summarized from Our Empirical Results

The Characteristics of CX Performance States				
	L State	**M State**	**H State**	**H+ State**
State Performance of Average Rating Score	**5.80**	**7.32**	**8.32**	**9.23**
The State Dependence of Four Dimensions of CX	· Negatively Determined by Affective CX	· Positively Determined by Cognitive CX · Negatively Determined by Affective CX and Social CX	· Positively Determined by Affective CX · Negatively Determined by Cognitive CX	· Positively Determined by Affective CX and Social CX · Negatively Determined by Cognitive CX and Physical CX

Dynamic CXM Strategies			
Goal: Increasing the Probabilities of Upward Migrations	**(1) Efficient ARCI Components**	**(2) Efficient Criteria on Booking.com**	**(3) Backfire Effects Decreasing the Upward Probabilities**
From L state to M state	· Increasing Positive Firm's Activities · Increasing Positive Interactions	· Increasing Qualities of Facilities	
From L state to H state	· Increasing Positive Firm's Activities · Increasing Positive Interactions		
From L state to H+ state	· Increasing Positive Firm's Activities	· Increasing Qualities of Facilities	
From M state to H state	· Increasing Positive Firm's Activities · Increasing Positive Contexts · Increasing Positive Interactions	· Increasing Qualities of Staff · Increasing Qualities of Facilities	
From M state to H+ state	· Increasing Positive Customer' Activities · Increasing Positive Contexts	· Increasing Qualities of Facilities · Increasing Comfort of Room	· The Perceived Firm's Resources · The Perceived Convenience of Location
From H to H+ state	· Increasing Positive Contexts · Increasing Positive Interactions		· The Perceived Firm's Resources · The Perceived Customers' Resources

For CXM application, we identify the four CX performance states in terms of state variable levels (the rating scores given by guest reviewers), which are determined by guests' perceptions during the current period of their stays at the focal hotels. We also model dynamic CXM migration strategies, identifying the managerial strategies that will promote upward migration and those that will deter downward migration; these are powerful tools for managers who have identified their own CX performance states. For example, for firms currently in the L state, managers should actively pursue the relevant firm actions and positive interactions with their guests. More importantly, managers need to prevent drift to the L state by regularly assessing whether their guests have perceived negative interactions. If there is a potential area that customers might perceive as a "negative interaction", managers need to react quickly before the CX performance transitions down to the "L" state.

4.5.3 Future Research

It will be useful for future research to integrate the perspectives of study 1 and study 2. Whereas the former employs the perspectives of the individual customers, the latter examines CX through the lens of the firm. Future research (study 3) will focus on integrating the perspectives of both the experience providers and experience receivers, aiming to elucidate the dynamic interactions between customer and firms.

Furthermore, we note some limitations of our research and make suggestions for future investigations based on them. First, the CX performance states we have presented here relate to a 13-week window and hence might be unrepresentative of the full spectrum of the CX performance cycle. Firms (especially hotels) might not exhibit dynamics within such a window. With the advancement of big data techniques, future research might attempt to collect longer-term data to gain a more comprehensive understanding of firm CX performance dynamics. Second, building on the notion of heterogeneity, it is possible that firms/experience providers differ not only in how they transition among the states and how they behave when in a given state but also in the number of states among which they transition. In other words, instead of developing an HMM with N states, one might consider an HMM with N_i states, i.e., a different number of states for each firm/experience provider. Similarly, a firm might move among a set of states due to exogenous factors (e.g., economic shocks, industry lifecycle) or endogenous events (e.g., the introduction of a new IT service system). Modeling such state generation and evolution would provide a better understanding of CX and firm CX performance dynamics over time. Finally, we suggest that scholars exploit the advantages of data fusion. One could use the latent state for data fusion by merging different sets of information at different time intervals using the common latent state. For instance, in our research settings, future research might integrate hotels' real transaction data (sales revenue, occupancy ratio), guests' online reviews, surveys collected at the front desk/reception desk, opinion cards left by guests in their rooms, and guests' calls to customer service to produce a more detailed picture of the experience providers' CX performance dynamics.

Chapter 5 Empirical Study 3

Dynamic Online Managerial Response Strategies

Abstract

Customer reviews receive much attention due to their strong links with firms' sales and online reputations. Firms can choose to respond to customer reviews, which not only affect the re-patronage decisions of current customers but also influence those of the potential/future customers who read the review thread. While a body of research has focused on exploring whether and how managerial responses (MRs) influence customer reviews (CRs), consensus has, surprisingly, not yet been achieved regarding the reverberating relationships and the dynamic influences of MRs on future CRs. To address this issue, we develop the "Online CR-MR Echoverse" framework to depict a bilateral communication environment between firms and customers in online settings. This CR-MR Echoverse integrates several theoretical lenses including emotion regulation, service recovery, and herding behaviors. The building blocks of the CR-MR Echoverse include distinct CR and MR components that comprise a reverberation system, portraying spillover effects of MR components on future CR components and herding effects among CR components. We collect customers' verbatim reviews and manager's textual responses from the TripAdvisor website using text-mining techniques and analyze them with VAR modeling. The empirical results support the existence of spillover effects and herding behaviors. We tailor different combinations of MR components to regulate customers' positive/negative emotions and rating behaviors. These findings provide

guidance for managers on how to design optimal MR strategies through distinct combinations of MR components.

5.1 Introduction

User-generated online reviews or online customer reviews (CRs) have gained increasing credibility for consumers to the extent that, today, they are an essential part of the consumer decision-making process (Chevelier & Hinckley, 2015; Luca, 2011; Mayzlin, 2006). 87% of consumers report that positive online reviews strengthen their purchasing decisions, while 80% report that negative online reviews have led them to change their minds (Duncan, 2011). The result is that online CRs have the potential to significantly affect product sales (Chevalier & Mayzlin, 2006; Clemons, Gao, & Hitt, 2006; Dellarocas, Zhang, & Awad, 2007; Moe & Trusov, 2011). Chen and Xie (2008) suggest that CRs can, in theory, work as sales assistants to help novice consumers identify the products that best match their idiosyncratic preferences, enabling them to make better informed decisions (Moe & Trusov, 2011). In practice, customers' negative online word of mouth (WOM), such as that which followed the United Airlines' passenger removal incidents, can go viral, damaging a firm's reputation and causing it to lose thousands of customers (Dunphy, 2012; Ward & Ostrom, 2006). Hence, firms are under increasing pressure to maintain their online reputation, engage with dissatisfied customers, respond to consumers' online reviews, and positively influence their customers' future experiences (Gu & Ye, 2014).

Indeed, the popularity and reach of online review platforms are so large-scale that the practice of publicly responding online to consumers has emerged as a strategy for reputation management. A management response (MR) is an open-ended piece of text that is permanently displayed beneath the review it addresses (Proserpio & Zervas, 2017). The entry of a firm into an online conversation can potentially change the nature of the discourse, which can in turn affect customers' incentives to post reviews (Chevalier et al., 2018). Thus, from the perspective of the poster (i.e., the customer reviewer), the potential audience includes not only other customers but also the firm and its managers. From the perspective of the firm/service provider, an understanding of the effect of MR on online reviews and future reviewing behavior may enable it to optimally achieve its managerial objectives by highlighting positive comments (to acquire potential customers and retain current clients) and mitigating negative comments (to prevent customer churn and online firestorms). However, previous contributions to the MR research stream have not yet reached a consensus regarding the impacts, underlying mechanisms, or pros and cons of MRs on future customer reviews and business performance (Chen et al., 2019; Chevalier et al., 2018; Herhausen et al., 2019; Kumar et al., 2018; Proserpio & Zervas, 2017). Firms are similarly unsure about how to use MRs in practice. An extensive survey of online reviews indicates that the use of MRs by firms remains limited (Chen, Gu, ,Ye & Zhu, 2019; Lappas et al., 2016; Levy et al., 2013). More specifically, 72% of firms rate their preparedness for online negative WOM as below average (Ethical Corporation, 2012; Herhausen et al., 2019) and the accuracy of this self-rating is borne out by the two-thirds of all negative reviews on TripAdvisor that do not receive responses from business (Lappas et al., 2016). Also, firms have diverse practices when using MRs (Park & Allen, 2013). Although researchers and practitioners have begun to recognize the critical role of managerial responses (MRs) to customer reviews (CRs), several knowledge gaps must be addressed in the existing literature.

First, studies on information systems and marketing have demonstrated the causal relationships between online CRs and sales. Recent studies show that the valence (sentiments) or volume of the CRs received during the previous periods can predict the sales of future periods (Archak et al., 2011; Dellarocas et al., 2007; Dhar & Chang, 2009). And this causal relationship works in the opposite direction, with studies reporting that product sales can also predict the valence and volume of online CRs (e.g., Li, 2011; Moon et al., 2010). Moreover, relationships (e.g., causal, interrelated, interactive effects) and mechanisms between CRs and MRs have been identified by previous researchers (e.g., Chen, Gu, Ye & Zhu, 2019; Chevalier et al., 2018; Duan et al., 2008; Herhausen et al., 2019; Johnen & Schnittka, 2019; Kumar, Qiu, & Kumar, 2018; Park et al., 2012; Proserpio & Zervas, 2017). However, to the best of our knowledge, few studies have investigated the interrelated temporal (lag) effects between online CRs and online MRs. **Second**, most of the extant studies have used volume (number), valence (sentiment), and content length to measure online CRs and MRs (Chen et al., 2019; Chevalier et al., 2018; Kumar et al., 2018; Proserpio & Zervas, 2017). We argue that a complete picture has not yet been obtained regarding the measure of MR/CR and their underlying mechanisms. In product/service rating settings, customers can go onto online platforms (e.g., Amazon, Yelp, TripAdvisor) and write verbatim reviews to which managers may choose to textually respond. These unstructured text data offer an opportunity to uncover a more complete measure of online CRs and MRs and gain deeper understanding of the underlying mechanisms and dynamics between CRs and MRs (Berger et al., 2020). Leveraging the advantages of text data, we combine the results of previous contributors with text mining techniques to capture the various, multifaceted compositional elements that comprise online CRs and MRs. **Third**, the existing MR research, save for the contribution of Herhausen et al. (2019), does not differentiate between the circumstances in which a specific expression of tone, content, or style of MR is relatively effective. Herhausen et al. (2019) have developed a comprehensive framework that integrates different motivations of online negative WOM and the MR approaches that firms can use to detect, prevent, and mitigate online negative WOM. Although the authors argue that when negative eWOM evolves into an "online firestorm", multiple MRs become necessary to mitigate the situation, they do not address whether the impacts exerted by the MR approaches will change and evolve over time. We therefore identify a gap in the MR literature concerning the necessity of viewing and developing MR strategies from a dynamic perspective. To close this gap, we try to explain how different MR strategies vary in terms of their effectiveness in dealing with the different facets of CRs. We propose that these effects are not static, but rather evolve and change over time. **Fourth**, most of the review sites (e.g., Yelp, Amazon, TripAdvisor) expose raters to the ratings of others. These prior ratings often influence current raters' evaluations, a process generally known as herding (Sunder, Kim, & Yorkston, 2019). Most CR research on herding has focused on the rising role of social influences/social dynamics in online settings or communities (Dellarocas & Narayan, 2006; Godes & Silva, 2012; Goes, Lin, & Yeung, 2014; Li & Hitt, 2008; Muchnik, Aral, & Taylor, 2013; Sridhar & Srinivasan, 2012; Wu & Huberman, 2008). Some works focus on parsing out the multiple sources of herding effects, such as a network of friends versus the general public (Lee, Hosanager, & Tan, 2015; Zhang & Godes, 2018). For example, a friend's rating may be more salient than the rating of the crowd, especially when the friend's interests overlap with those of the focal rater. Other research explores the contingencies under which herding may or may not occur (Sunder et al., 2019), highlighting differences in the herding effects across multiple reference groups. Still, there is no empirical research that explores the co-existence of online MRs and previous CRs on future CRs. We try to break new ground by examining the herding effects exerted by previous raters' evaluations (firm-uncontrollable factors) on future raters' evaluations, while simultaneously considering the influences of different facets of online MR strategies (firm-controllable factors). These four points highlight the gaps in the extant literature that motivate our study.

To systematically bridge these gaps and contribute to the MR literature, we leverage Hewett et al. (2016)'s concept of the "echoverse", which depicts an online communication environment where the experience providers (firms) and experience receivers (customers) communicate through CRs and MRs, reflecting the dynamic relationships between the two parties. In this research, our customers (the experience receivers) are those who contribute to the communication environment by posting online reviews (CRs). Firms, as the other party in the relationship, can contribute to the echoverse by posting online MRs in response to these customers' CRs. We propose an "Online CR-MR Echoverse" framework to investigate the dynamics between online CRs and online MRs. Our research context focuses on a dynamic service provision setting. This is because static-quality products, such as laptops or books, generate online reviews that amount to an information sharing channel, and there is very little that a manager can do to change time-invariant product quality. By contrast, in the case of dynamic-quality services, such as those provided by hotels or restaurants, managerial investment may alter the service quality over time, and is often prompted to do so by clients' online reviews (Chevalier, Dover, & Mayzlin, 2018). Specifically, we ask the following research questions: (1) What are the major elements of online MRs and online CRs, respectively, that firms aim to influence? After thus identifying the crucial components of online CRs and online MRs, the many different elements of MRs mean that service providers must pinpoint the following: (2) What are the different effects of the various components of online MRs on the distinct elements of online CRs? and what are the herding effects among online raters? Finally, (3) how do we model the above results to identify MR strategies that can effectively promote positive CRs or suppress negative ones, thereby generating dynamic online MR strategies? Addressing these questions will foster a complete theory of dynamic MR strategies in the service provision context. In this paper, we attempt to advance our understanding of whether the many facets of MRs in the online review environment influence the positive/negative emotions and rating behaviors of future customers, and the possibly underlying mechanisms for developing effective, dynamic MR strategies.

5.2 Literature Review and Conceptual Framework

5.2.1 Existing Studies on Online Managerial Responses (MRs) to Online Customer Reviews (CRs)

To help place the intended contribution of this study in context, we briefly review the previous empirical research on the effectiveness of online MR. In this section, we review the MR literature from three different perspectives: (1) the impact of online MR on business performances; (2) the dynamics between online MRs and CRs; and (3) the varying effectiveness of different MR designs.

We first consider the nascent literature related to the research stream that concerns the impact of MR on business performance. Kumar, Qiu, and Kumar (2018) examine the impact of online MRs on the focal firm’s business performance and their spillover effects on the business performances of the firm's direct and indirect competitors. Kumar et al. (2018) find that MRs play a significant role in the performance of the focal firm. They also establish that the spillover effect (externality) of online MRs on nearby businesses crucially depends on whether the focal business and the businesses nearby are in direct competition with each other. Ye et al. (2008) find that MRs affect future CRs by impacting on sales because MRs may highlight positive reviews and mitigate the impact of negative ones. Thus, MRs increase future sales, given that consumers rely on reviews to evaluate products prior to purchasing them (Ho et al., 2017). Recent research shows that MRs may indeed increase sales (Kumar et al., 2018; Xie et al., 2014), and that one of the underlying mechanisms for this is related to service recovery (e.g., Lewis & McCann, 2004; Maxham III & Netemeyer, 2002) since this focuses on customers' complaints to prevent the negative effect from spreading (Kelley & Davis, 1994). Kim et al. (2015) use proprietary data from an international hotel-chain and show a correlation between the responses to negative comments and hotel performance.

In the literature on the dynamics between CRs and MRs, Gu and Ye (2014) empirically study the responses hosted on a third-party review website in China and find that MRs to CRs with low satisfaction have a positive influence on hotels' future online ratings. However, the impact of such responses on other customers is found to be limited. Moreover, Gu and Ye (2014) show that MRs positively influence repeat customers, although they also find that such responses decrease the satisfaction of other customers. However, since the study focuses on repeat customers, the impact of MRs on a broader audience is not clear. Chen, Gu, Ye, and Zhu (2019) use a unique research design, matching hotels across two large travel agencies, and find that MRs have a significantly positive impact on the volume of subsequent CRs but that the impact on the CRs' valence is not evident. Proserpio and Zervas (2017) find that MR increases both the volume and valence of positive CRs. They find that MRs encourage consumers to post more positive reviews and a smaller number of negative ones because consumers who post positive reviews may feel that their feedback is appreciated while those who post negative ones know that their feedback will be scrutinized. Furthermore, Proserpio and Zervas's findings highlight an interesting trade-off related to using MRs, in that they will give rise to an increased number of positive CRs with better ratings but this is at the cost of longer, albeit fewer, negative reviews. Chevalier, Dover and Mayzlin (2018) examine the effect of MRs on CRs and the consumer voice in a dynamic quality environment. They find that MRs will stimulate reviewing activities (i.e., the volume of CRs), particularly negative reviews, because managers respond more often and in greater detail to negative reviews. Several other papers in this area have examined the effect of MRs on hotel CRs. For example, Park and Allen (2013) use a case study of four luxury hotels and investigate why the managers choose to be active or inactive in terms of their responses. Kim et al. (2015) use proprietary data from an international hotel-chain and indicate an association between MRs to negative CRs and hotel performance. Ye et al. (2018) use data from two Chinese travel agents and show that reviewing activity (CR volume) and valence increase for hotels that post MRs.

Regarding the third research stream on the varying effectiveness of different MR designs, Chen et al. (2019) find that responding to positive and negative CRs has different effects on future CRs, suggesting that managers should provide detailed MRs to negative CRs but brief MRs to positive ones. Evans et al. (2012) conduct an experimental study to test the effectiveness of MRs to negative reviews by analyzing readers' propensity to visit a restaurant. They find that readers are least likely to visit a restaurant after seeing no response to a negative comment. However, positive and constructive MRs can decrease the damage caused by a negative review. Xie et al. (2017) find that different designs of MRs may matter for different classes of hotels. Merely responding is not sufficient since improper responses may backfire. Xie et al. (2017) argue that managers must respond to the type of CR with the right type of MR. Chen et al. (2019) find that, when responding to negative reviews, managers must be specific in either explaining what has happened with the customer or disclosing the improvements made following the incident. Herhausen et al. (2019) find that MRs must be tailored to the intensity of arousal in negative CRs to limit the outbreak of potential online firestorms. They further find that the impact of negative CRs can be mitigated by using distinct MRs over time and that the effectiveness of different disengagement MR approaches also varies with their timing. When firms provide more substantiated arguments, this may enhance customers' perceptions of the response quality and efforts. By providing a fuller explanation, firms might enhance the evaluation of their recovery efforts (Bitner, Boorns, & Tetreault, 1990). To conclude, previous researchers agree that MRs can increase future sales and the volume of CRs. However, there is still debate about how to increase the valence of CRs. Several scholars argue that MRs increase the overall valence of CRs (i.e., they reduce the posting of negative reviews) since reviewers are worried that their reviews will be scrutinized in depth (e.g., Proserpio & Zervas, 2017). Others argue that MRs decrease the valence of CRs (i.e., they stimulate negative reviews) because potential reviewers perceive negative reviews to be more impactful (e.g., Chevalier et al., 2018). In short, the dynamic nature of MR strategic designs is not well understood in that the results are fragmented across a variety of research settings.

Although existing CR/MR studies have examined the effectiveness of the presence of MRs, they do not differentiate the circumstances in which a certain type of response is more effective for certain types of reviews. Specifically, to date, no empirical work has shed light on the (longitudinal) changing effects of MRs on positive CRs versus negative CRs. Moreover, although literature has pinpointed the social influence (or herding influences) on CRs (Moe & Trusov, 2011; Sridhar & Srinivasan, 2012; Sunder et al., 2019), there are no insights into the dynamics of MRs and future CRs that simultaneously take into account the herding effects seen in CRs. To solve these issues, we need to understand the building blocks of CRs and MRs. We can then develop dynamic MR strategies to fulfill specific managerial objectives. Sections 2.2 and 2.3 build up the theoretical grounds that underpin a more comprehensive understanding of the components of MRs and CRs. Section 2.2 applies the theoretical lens of positive emotion regulation, negative emotion regulation, and similarity perception between CRs and MRs, as well as examining herding behaviors among CRs. In this way, we aim to provide a solid grounding for our focal CR and MR components in Section 2.3.

5.2.2 The Need to Leverage Theoretical Perspectives to Interpret MR and CR Components

Extant marketing research has described the spreading of online content as an emotionally contagious process in which receivers "catch" the emotion of others through social transmission (Berger, 2014). The process depends on the sender's emotions

(Berger & Milkman, 2012; Heath, Bell, & Sterberg, 2001) and the relationships between the senders and receivers (Brown & Reingen, 1987; Mittal, Huppertz, & Khare, 2008). Specifically, Berger and Milkman (2012) have indicated that positive CR content is more viral than negative CR. Some studies have applied these insights in the context of online managerial responses to customer reviews. Research has suggested that the relative transmission of online WOM is a result of the contagiousness of the heuristics related to the sender's message (Brown & Reingen, 1987; Heath, Bell, & Sternberg, 2001; Mittal, Huppertz, & Khare, 2008). For example, the increased use of affective words in a post efficiently reveals and makes accessible the customer's intent or the raw feelings underlying the post (Cohen et al., 2008). Increasing the number of negative emotion words in CRs translates directly into stronger behavioral responses from the message recipients (Ludwig et al., 2013). Even if the content is unrealistic, more negative emotional messages are more frequently shared (Blaine & Boyer, 2018). In addition to interpreting the emotional contagion phenomenon between online CRs and MRs, firms must go further and pinpoint how to respond to customers' online reviews. That is, firms must craft their online response strategies to minimize the effects of negative comments or to maximize the effects of positive comments on the wider audience of potential customers in online contexts. Emotional contagion theorists assert the importance of interpersonal relations that enable message recipients to evaluate others and devise appropriate responses (Barsade, 2002).

5.2.2.1 Regulating Positive Emotion to Maximize the Effects of Positive Comments.

Previous research has indicated that customers report on their positive experiences because doing so elicits pleasurable feelings. For example, Dichter (1966) argues for

WOM as "verbal consumption", allowing people to relive the pleasure the speaker has obtained. Langston (1994) found that communicating a positive event to others enhanced positive affect, even above and beyond the affect associated with the experience itself (see also Gable, Reis, Impett, & Asher, 2004). People may share emotionally charged content to make sense of their experiences, reduce dissonance, or deepen social connections (Festinger, Riecken, & Schachter, 1956; Peters & Kashima, 2007; Rime et al., 1991). Consumers share positive CRs for self-presentation purposes (Wojnicki & Godes, 2008) or to communicate identity and thereby impact on diffusion and sales (Godes & Mayzlin, 2004; 2009; Goldenberg et al., 2009), or to generate greater WOM (Anderson, 1998), or to help boost others' moods or provide information about potential rewards (Berger & Milkman, 2012).

Although the CR literature has examined the motivations and effectiveness of customers' sharing of positive CR in online contexts, there is limited empirical work examining how to tailor managerial responses to positive online comments and maximize their influences. Some researchers consider language use, investigating the use of explaining language (Moore, 2012), expressions of modesty (Packard, Gershoff, & Wooten, 2012), personal pronoun usage (i.e., "I" versus "you," Packard & Wooten, 2013; Packard, McFerran, & Moore, 2014), language complexity (Packard & Wooten, 2013), and linguistic mimicry of conversation partners (Moore & McFerran, 2012). For example, customer service representatives tend to use "you" or "we" rather than "I" when talking to customers. Surprisingly, Packard et al. (2014) argues that using "I" actually enhances satisfaction and purchase intentions.

Another theoretical perspective is related to the perceived benefits provided by the firm to potential customers/online observers. When a firm provides the benefits that are being sought out by consumers, the consumers express more favorable behavioral intentions toward it (Dawson et al., 1990; Hilken et al., 2017). Thus, managers need to determine what benefits the potential customers/online observers are seeking and how combining the positive CR with the appropriate MR might help online observers to attain these sought benefits. We argue that by offering content (i.e., an MR) that is linked to online observers' sought benefits, firms can address the observers' specific goals, thereby influencing their expectations and mindsets (Förster et al., 2007). For example, potential customers may be pursuing hedonic benefits, derived from subjectively pleasant personal consumption experiences involving entertainment, enjoyment, and positive emotions. Or they may be mere observers seeking utilitarian benefits, such as useful information, the resolution of problems, or valuable aids. These different sought benefits should create different expectations of the appropriate MR, although no prior research has offered empirical evidence for how MR could address these varying benefits sought by potential customers/online observers in a positive CR. We thus contend that much more research is required if we are to understand how to amplify/regulate customers' positive emotion through an MR designed to satisfy potential customers' sought benefits.

5.2.2.2 Regulating Negative Emotion to Minimize the Effects of Negative Comments.

Consumer complaints are widespread in online settings. Generally, a complaint refers to a behavioral "expression of dissatisfaction" (Kowalski, 1996). These complaints, publicly visible to numerous observers, can have detrimental impacts on a firm's reputation and sales (e.g., Rosario et al., 2016). To reduce the contagiousness of negative CR, research on service recovery provides approaches for restoring relationship equity to the complaining customer, which can curb a negative CR message from spreading to other online customers. For example, the offer of an apology or compensation, or giving an empathic response or explanation has been investigated in a firm-customer communication context (e.g., Hill, Roggeveen, & Grewal, 2015). Drawing on emotion regulation strategies (Gross & Thompson, 2007), Herhausen et al. (2019) further propose strategies to reduce the contagiousness of emotions in negative online CR. According to Herhausen et al. (2019), the disengagement approach to emotion regulation implies reacting in ways that avoid or block elaboration rather than preparing an adaptive response (Sheppes et al., 2011). For example, firms can try to halt an ongoing public online conversation by suggesting a communication channel change. However, Herhausen et al.'s active engagement extends from the service recovery literature and outlines two primary response approaches that represent active firm-customer conversational elaboration (Hill, Roggeveen, & Grewal, 2015): empathic and explanatory.

Nevertheless, the literature has been unable to definitively identify the most effective approaches for engaging and disengaging. Some of the service research has suggested that halting further elaboration by offering compensation is an effective recovery strategy (e.g., Bitner, Booms, & Tetreault, 1990) whereas Grewal, Roggeveen, and Tsiros (2008) find that the effectiveness of offering compensation depends on other response features. Regarding the strategies of engagement, Homburg, Grozdanovicm and Klarmann (2007) posit that empathy is more effective in affect-intensive environments characterized by social interactions and spontaneous decisions. Indeed, the research on emotion regulation strategies indicates that some stimuli may be too emotionally intense for an empathic response to suffice, and that the recipients of empathy may seek explanations enabling them to reappraise the situation (Gross, 2002) and may also have higher expectations for the appropriate remedies (Hess, Ganesan, & Klein, 2003). Herhausen et al. (2019) argue that empathic responses help shift the attention of consumers experiencing low-arousal negative emotions but that firms will better mitigate the virality of high-arousal negative emotions if they offer explanations.

Other research considers response strategies from the accommodative or defensive perspectives (Marcus & Goodman, 1991). The distinction is based on whether or not the firm acknowledges responsibility for the complaint (Kim et al., 2004). An accommodative response signals that the firm accepts responsibility by offering an apology, compensation, corrective actions, helpful information, or by expressing regret (Davidow, 2003). The defensive response rejects responsibility and includes indicators such as denial, doubts, excuses, trivializing, or accusations (Conlon & Murry, 1996; Marcus & Goodman, 1991). Previous studies show that an accommodative response strategy appears preferable for evoking positive outcomes such as consumer satisfaction, favorable evaluations, and increased purchase intentions (e.g., Chang et al., 2015; Xia, 2013), based on the rationale that complainants appreciate the direct or indirect assumption of responsibility by the firm (Coombs, 2007; Davidow, 2003). It can also be argued, from the lens of the potential customers/online observers, that the effectiveness of an accommodative response strategy arises because the widespread audience identifies with the complainant in developing similar expectations (Chang et al., 2015), expressing higher levels of perceived justice (Rose & Blodgett, 2016) and lower levels of attributed controllability (Chang et al., 2015), thereby decreasing negative emotions (Xia, 2013).

Since there are inconsistent suggestions in the literature regarding negative emotion regulatory strategies, we aim to close this gap in our empirical study. First, in line with previous research, we hypothesize that responding leads to more favorable outcomes than remaining silent, because potential customers/online observers appreciate a firm's willingness to interact with its consumers, which signals respect and professionalism (Weitzel & Hutzinger, 2017). Second, we argue that in online contexts, the anonymity of the CR posters, firm managers, and other audiences/potential customers means that the firm communication might first need to develop a psychological synchrony that elicits perceptions of similarity, approval, and trust in the MR recipient (Ireland & Pennebaker, 2010) through expressions of affective words and empathy. After building this affective/empathic foundation, firms can then trigger customers' cognitive re-appraisal processes by issuing a further component in the remaining content, such as offering explanations or providing remedies that mitigate posters' negative emotions. Thus, we argue for a mixed message with varying combinations of affective infusion, cognitive appraisal, empathy, and explanation expressions in MRs toward negative CRs.

5.2.2.3 Leveraging the Similarity Perceptions between MRs and CRs.

Similarly, the marketing research on WOM suggests that perceptions of similarity cause receivers to regard senders as more proximate and psychologically synchronized (Brown & Reingen, 1987; Ireland & Pennebaker, 2010). For example, Aral, Muchnik, and Sundararajan (2009) find that perceptions of similarity between customers explain more than half the effect of behavioral contagion on new product adoption. Ireland and Pennebaker (2010) find that similarity perception elicits approval and trust in message receivers. Moreover, studies drawing on psycholinguistic research suggest that perceptions of similarity in computer mediated settings are an automatic outcome of a linguistic style match. That is, the similar use of function words, or the linguistic style match between two conversation partners, represents a form of psychological synchrony that elicits perceptions of similarity, approval, and trust in receivers (Ireland & Pennebaker, 2010). Although the existing research has confirmed that an individual customer's alignment with a community-level style may elicit similarity perceptions and in turn influence the approval likelihood by the collective (Fayard a& DeSanctis, 2010; Gumperz & Levinson, 1996), no empirical work has examined the effects of similarity perception between CR and MR. We argue that the more the writing tone and linguistic style of the MR aligns with the focal CR's communicative style, the more the customer will perceive a feeling of similarity, and this will be passed on to other potential audience members.

5.2.2.4 Proposing the Compositional Elements of MRs and CRs

Following the reasoning in sections 2.2.1-2.2.3, we adopt several related theoretical perspectives that might help to achieve the research goal in this paper, which is to identify the critical elements of MRs and CRs that can lead to the effective design of MR strategies. The theoretical lenses that can potentially help to identify focal CR/MR components include emotional regulation, cognitive appraisal, affect infusion, similarity perception, and service recovery perspectives. The viability of the common recovery approaches—offering an apology or compensation, responding empathically, or providing an explanation—have been investigated mainly in firm-customer communication contexts (e.g., Hill, Roggeveen, & Grewal, 2015). Specifically, to regulate customers' negative emotion, the literature has outlined two primary response approaches: empathic and explanatory. To express empathy, i.e., a spontaneous affective response, a firm might sympathize (e.g., we understand that you are unhappy) or shift to a positive outlook (e.g., we hope you will have a better experience next time). An engaged MR also might include substantiated explanations, and increasing the number of reasons offered has more influence on the decision outcomes than the actual content of those reasons (Seibold, Lemus, & Kang, 2010). In line with cognitive appraisal theory and the affect infusion model, Homburg et al. (2007) note that an affective approach, such as empathy, is more effective in an affective-intensive environment. The research in other areas has also shown that firm communications affect performance through consumer sentiment (Bart, Stephen, & Sarvary, 2014; Zarantonello, Jididi, & Schmitt, 2013).

In **Table 5.1**, we present a comparison chart of five prior works that are directly related to our research topic. As the table shows, the first four studies use similar means to capture, measure, or infer MR and CR. The last study, which was conducted by Herhausen et al. (2019), goes beyond the traditional measuring approach, and leverages computerized text analysis in a top-down manner, using existing LIWC dictionaries and newly developed dictionaries, and it is this strand of research that inspires this study to capture the compositional elements of MR/CR by employing a text mining technique and dictionary-based analysis. **Table 5.1**, presented below, summarizes the previous contributions from the literature on MR/CR.

Table 5.1 Comparison of Existing Empirical Studies on the Elements of MR and CR

Studies	Variables/Elements Related to Online MR	Variables/Elements Related to Online CR
Chen, Gu, Ye and Zhu (2019)	· Whether hotel i has adopted MR in the sample · Whether hotel i has adopted MR by month t	· Number of new CRs · Mean valence of CRs · Total number of CRs · The cumulative mean valence of CRs
Kumar, Qiu and Kumar (2018)	· Binary MR variable indicating whether business i responds to customers' comments in month t	· Average review rating · The standard error of review rating · Average CR length · The number of CRs
Chevalier, Dover, Mayzlin (2018)	· MR response rate	· Number of CRs · Mean rating
Proserpio and Zervas (2017)	· Number of MRs per hotel · Average MR length	· Average hotel rating · Number of CRs per hotel · Average CR length
Herhausen, Ludwig, Grewal, Wulf, and Schoegel (2019)	· Intensity of empathy · Intensity of explanation · Variation in MRs: variance in the proportion of empathic and explanatory words across all MRs · Compensation · Apology · Channel change	· The intensity of high arousal in CRs · The intensity of low arousal in CRs · Variance in linguistic style · The sentiment of previous CRs · CR length · CR complexity: average words containing more than six letters per sentence · Negation in CRs: "negate" in the percentage of total words · Previous complaints from the same customer · No firm response: dummy coded · Firm response time: the timestamp of the CR minus the time stamp of the MR

Building on our literature review in sections 5.2.1 and 5.2.2 and the previous contributions presented in **Table 5.1**, we suggest the following compositional elements for online MRs and CRs. In an extension of Herhausen et al. (2019)'s work, we consider four major categories comprising firms' online MRs: (1) the presence of MR; (2) its length; (3) the linguistic style including tone, linguistic style matched with that of the customer, variation in words across all firm responses; and (4) its contents, including the expression of thanks, offering apologies, expressing sympathy, offering explanations, providing remedies, offering compensation, and showing sincerity.

In terms of the compositional elements of online CR, extant CR research has described a contagion process, in which receivers catch others' "emotions" through social transmission (Berger, 2014; Berger & Milkman, 2012; Heath, Bell, & Sternberg, 2001). In addition to this theoretical aspect, we also consider the practicalities of a manager's primary objective for responding to a CR, which is to send out signals to potential consumers. We argue that one way to figure out the critical components of the CR is to consider what elements in CRs are emphasized/valued most by the firms. We thus hypothesize that firms aim to send signals to potential customers that the good experience described in positive CRs will be repeated for them, while the bad experience described in negative CR is unlikely to be repeated. Thus potential customers are encouraged by the reviews to view the firm in a more favorable light and give the business their patronage. In addition to a rating score, CRs that contain complaints, compliments, expressions of repurchasing or revisiting intentions, and recommendations are crucial from the business perspective. Integrating the emotion regulation perspective with the previous contributions in **Table 5.1** and the rating behavioral variables that are important to managers, we propose that there are seven major compositional elements of online CR: (1) positive emotions, (2) negative emotions, (3) rating score, (4) compliments, (5) complaints, (6) revisit intentions, and (7) referrals.

5.2.3 Proposing the Conceptual Framework

Finally, to develop an online communication environment that depicts dynamic customer-firm interactions, we adopt the concept of the "echoverse" from Hewett et al. (2016). We propose a conceptual framework, namely, the "Online CR-MR Echoverse", which we describe as a reverberating communication environment that forms complex "echoes" among actors. In our research setting, firms (as one source of actors) contribute to the communication system by posting online MRs, and customers (as the second source of actors) contribute through online CRs. Distinct components are associated with the customers' online CRs and firms' online MRs, as discussed in Section 5.2.2. In this section (Section 5.2.3.1-5.2.3.2), we further explore the herding effects among CRs and the potential effects exerted by MRs on future CRs to help develop an overarching conceptual paper in Section 5.2.3.3.

5.2.3.1 Leveraging the Herding Theory to Extract Herding Effects among Online CRs

To better regulate customers' emotions and their rating behavior by developing effective MR strategies, we further consider the herding effects among online raters, which occur when the prior ratings of others influence current raters' evaluations (Ding and Li, 2018; Sunder et al., 2019). Researchers have used the terms "social dynamics" (e.g., Moe & Schweidel, 2012; Moe & Trusov, 2011), "peer effects", "social multipliers" (e.g., Nair, Manchanda, & Bhatia, 2010), "social influences" (e.g., Godes & Silva, 2012; Goes, Lin, & Yeung, 2014), and "information cascades" (e.g., Lee, Hosanagar, & Tan, 2015) to describe the same behavior. The theory of herding (Banerjee, 1992;

Bikhchandani, Hirshleifer, and & Welch, 1992) is concerned with how social influence manifests in online rating environments. Typically, the research on herding in online rating has focused on social influence as an aggregate whole. Sunder et al. (2019) further focus on parsing the herding effects from multiple sources, highlighting the differences in herding effects across multiple reference groups. However, no empirical work differentiates social influences/herding effects from MR influences on customers' (future) rating behavior in online rating environments. We aim to close this gap by arguing that researchers should consider the herding effects between online raters to measure the effectiveness of specific MR strategies.

5.2.3.2 Leveraging the Link between MRs and Customers' Future Rating Behaviors

Proserpio and Zervas's (2017) study shows that there is a consistent increase of 0.12 stars in customers' ratings and a 12% increase in review volume after firms start using management responses. Their results highlight an intersecting trade-off, finding that fewer negative ratings can be achieved at the cost of longer and more detailed negative feedback posts. Chen, Gu, Ye and Zhu (2019) find that MRs have a significant impact on subsequent customer reviews, with an increase of 12% to 14% in review volume after a firm provides MRs. However, Chen et al. (2019) further analyze the time effects and reveal that the influence of MRs is not permanent. If the firm ceases to post MRs, the effect on future CR volume will decay over time. They also find that the MRs to positive and negative CRs have different effects on future reviews. That is, detailed MRs that focus on the minutiae of the reviewer's comments are essential for negative reviews but a similar level of detail may attenuate an MR's effect on positive CRs.

A number of field and lab studies (Bolton et al., 2013; Dellarocas & Wood, 2008; Resnick & Zeckhauser, 2002) have shown that in online settings where sellers and buyers can rate each other, negative ratings are underreported because of a fear of retaliation. However, when the option for sellers to leave negative feedbacks for buyers is removed, sellers start to receive an increased number of negative reviews (Hui et al., 2016). Gu and Ye (2014) find that a managerial response to a dissatisfied customer's review will have a positive influence on that customer's future online rating. However, the impact of the MR on other customers/potential customers is found to be limited. That is, although online MRs can positively influence repeat customers, they can also decrease the satisfaction of other customers. However, since Gu and Ye (2014) focus on repeat customers, the impact of MRs on a wider audience is not clear.

Chevalier et al. (2018) find that MRs stimulate reviewing activities and in particular, stimulate negative CRs that are seen as more impactful; this is based on the argument that managers respond more often and in more detail to negative reviews while reviewers receive a credible signal that the service provider is listening. Ma et al. (2015) examine the effect of a firm's service intervention in response to a compliment or a complaint on Twitter on the consumer's subsequent Twitter comments. Ma et al. (2015) find that redress seeking is a major driver of complaints, and hence an intervention may actually encourage future complaints.

As we discuss in this section, there are contradictory findings regarding MRs and the consequential CRs. Proserpio and Zervas (2017) find an increase in review valence following an MR on TripAdvisor. By contrast, Chevalier et al. (2018) find a decrease in review valence following the initiation of MR. The former suggests that the MR decreases the posting of negative reviews since reviewers become worried that their reviews will be more scrutinized and once hotels start responding, they attract reviewers who are inherently more positive in their evaluations. The latter argues that negative reviews are more likely to be stimulated by MRs since potential reviewers perceive negative reviews to be more impactful. And therein lies the manager’s dilemma, as identified by Chevalier et al. (2018). On one hand, an MR to a negative review may neutralize its possible negative effect on future bookings and customer evaluations. On the other hand, by responding to negative CRs, the firm also runs the risk of encouraging critical/negative reviews in the future.

This uncertainty about the pros and cons of MR that has been identified in the research and experienced by businesses has motivated the goal of this study, which is to assess the effectiveness of MRs on future CRs and investigate the underlying mechanism that triggers the influences.

5.2.3.3 Proposing the Online MR-CR Echoverse Framework

In this paper, we aim to answer the following three major research questions: (1) Given the different elements of MRs, what are the “spillover” effects of MRs on the distinct elements of online CRs? Moreover, (2) can we extract “herding effects” of online raters through an examination of online MRs? (3) How do we model the above results to identify MR strategies that can highlight the positivity or mitigate the negativity of online CRs?

To contribute to the MR/CR literature, we focus on parsing MR influences on customers. We argue that different MR components may exert different influences on different components of CRs. We therefore explore the contingencies under which MRs may or may not be effective at regulating customers' emotions and rating behaviors. We aim to understand the herding effects within online CRs and the spillover effects of MR components on future CR components, detecting the dynamics/reverberation system between online MR components and online CR components. Thus, we theorize the reverberation system of the "Online CR-MR Echoverse" (see **Figure 5.1**).

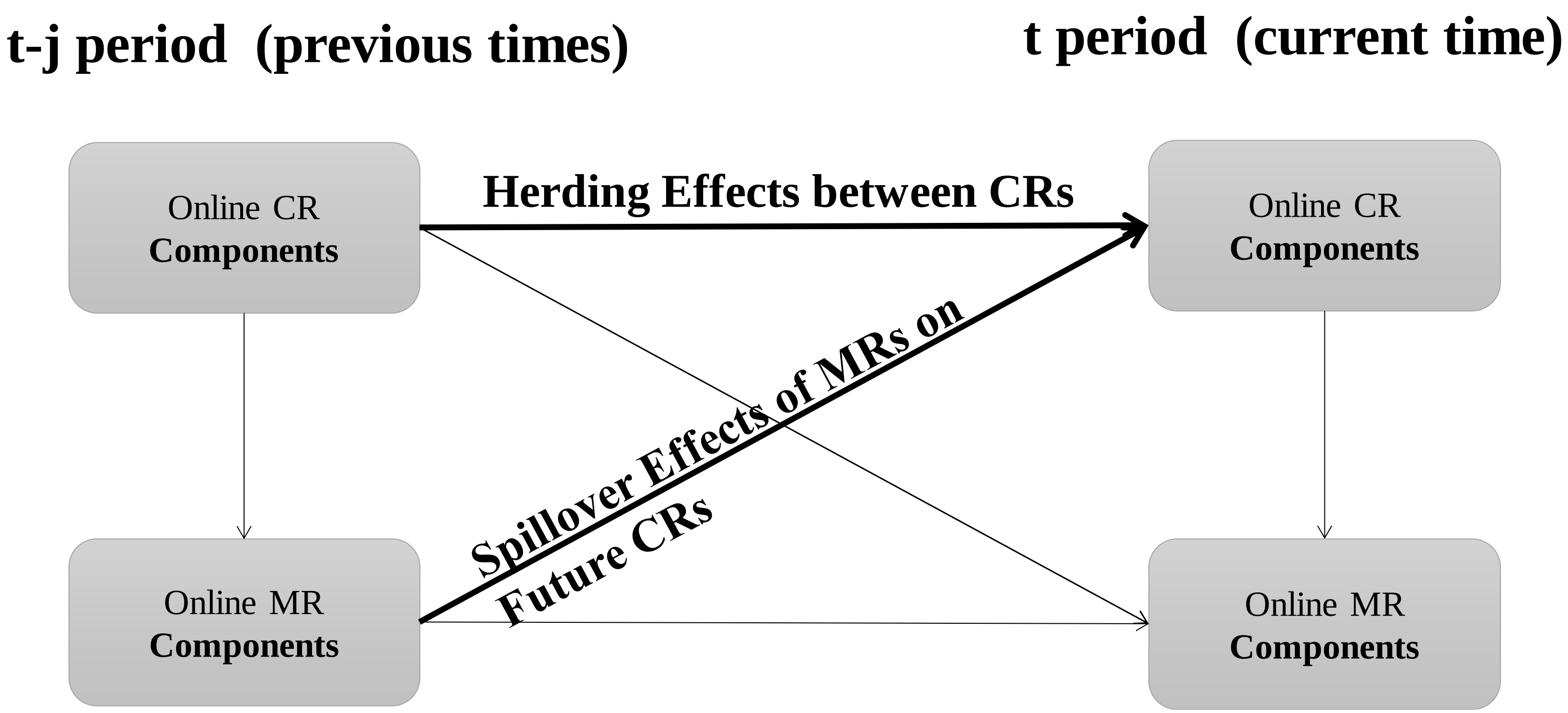


Figure 5.1 Online CR-MR Echoverse

Moreover, in **Figure 5.2**, we further conceptualize the specific MR/CR components in this study, indicating the herding effects among CRs and the spillover effects between MRs and future CRs, and applying several theoretical lenses to regulate focal CR components including customer emotions and rating behaviors.

In the proposed Online CR-MR Echoverse framework, we consider the effect of an online MR on the customers' online CRs. We refer to this process as the "spillover effect." We hypothesize that the spillover effect exerted by MRs can improve later customers' rating performances, such as rating scores, recommendations, or revisit intentions. We propose that MRs will exert a positive spillover effect on future CR performance through firms' consideration of customer emotion and rating behavior regulation. We hypothesize that firms will use amplifying MR strategies to regulate customers' positive emotions and will provide service recovery actions to regulate customers' negative emotions. For example, firms may amplify customers' positive emotions by employing a similar linguistic style or tone, or adopting the customers' affective expressions. Firms may attenuate the negative emotions of non-repeat customers by dynamically responding with one MR that offers mixed messages, such as a combination of affective or empathic expressions with cognitive or explanation components. In this research, we also consider customers' herding behaviors and argue that the effectiveness of a firm's MR strategy should take into account the herding effects among online raters.

Finally, we aim to outline the evidence gathered for this research and discuss its implications for building and executing dynamic MR strategies. We will develop research tenets to capture insights from our empirical results and inform an emerging theory of an

Online CR-MR Echoverse. We will list the guidelines that managers can use to devise the relevant MR strategies for triggering positive carryover effects on repeat customers or positive spillover effects on the wider customer base. The empirical results offer several managerial implications including: the positive emotion regulatory strategies for current and future/potential customers, the negative emotion regulatory strategies for current and future/potential customers, and the combinations of MR components that most positively influence customers' future rating behaviors.

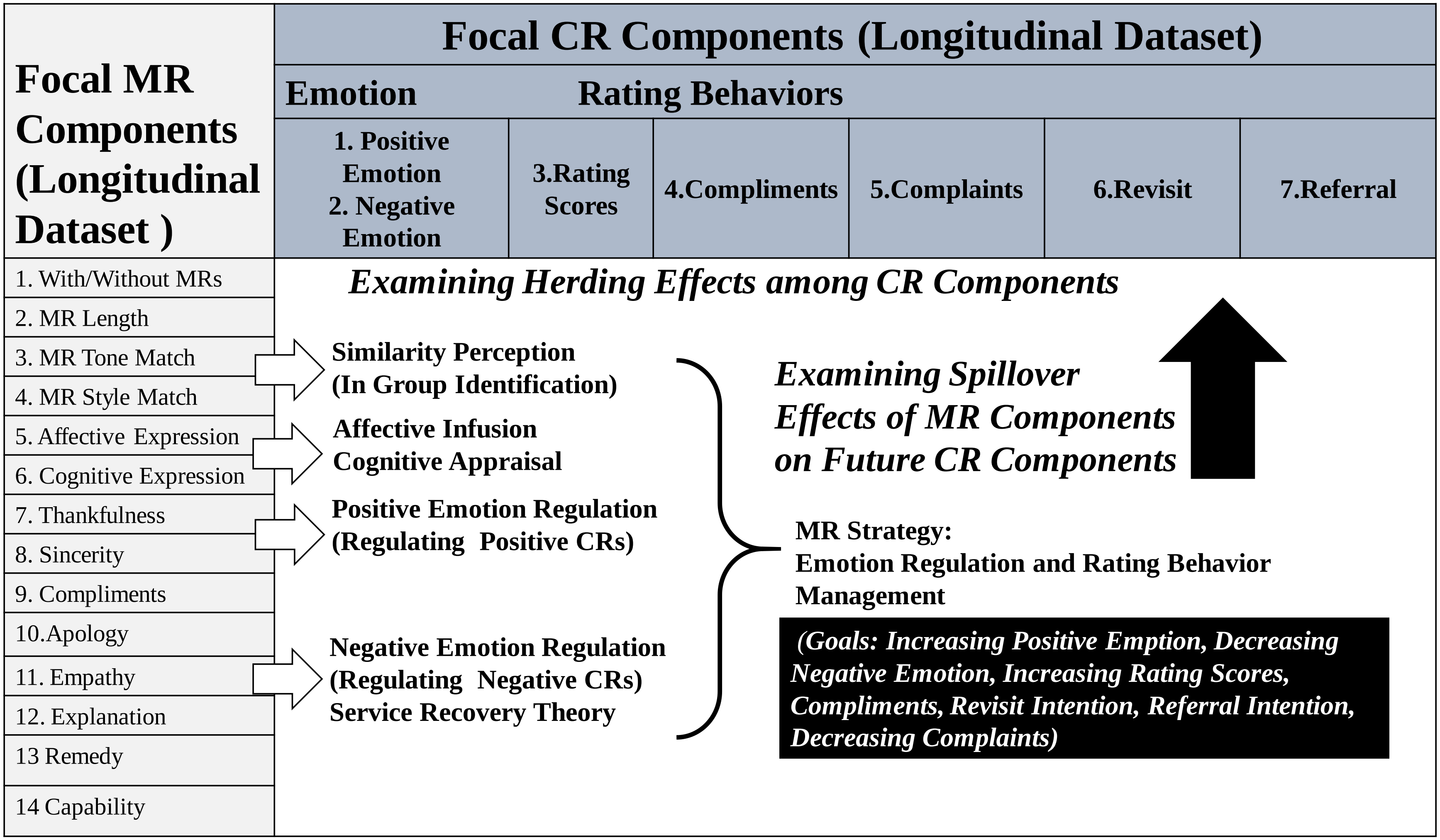


Figure 5.2 The Conceptualization of Focal MR/CR Components and the Research Foci of Spillover/Herding Effects

5.3 Methodology

5.3.1 Data Collection

Our major empirical context is the TripAdvisor website, which is the largest and best known travel website. It allows customers to provide online reviews for, *inter alia*, hotel stays, and allows hotel managers to respond to the customer reviews. There are clearly sampling issues to be considered. In addition to two self-selection issues where (1) hotels self-select whether or not they respond to CRs; and (2) hotels choose the CRs they respond to and the way in which they do so, the big data realm has its specific sampling problems. Unlike the traditional estimation problem where the sample size is generally not very dissimilar to the data size, with big data even a small sample relative to the size of the total data is extremely large and costly to obtain. A single website can easily generate data in the magnitude of billions, and directly accessing the entire dataset listed on the TripAdvisor website is neither possible nor computationally feasible. In practical terms, sampling seems to be a realistic approach to exploring large datasets. An evaluation of the most common data science software and packages shows that random sampling is frequently the only supported sampling technique for use with the large-scale datasets (Hall et al., 2009; Pedregosa et al., 2011; Travis, 2007). We therefore deal with these challenges of computational capacities and non-random choices through use of the Python random sampling algorithm. TripAdvisor lists 884 properties in Los Angeles, of which we collected 10% (88 hotels) through a random sampling algorithm. We employ Python algorithms to scrape/collect the consumers' online reviews, their rating scores, and the hotels' responses (if they did respond) from the sample hotels, resulting in a total of 44,650 comments and individual rating scores and 32,257 responses given by these hotels' managers from 1st July 2018 to 31st August 2019. We choose Los Angeles because it is one of the 10 largest U.S cities according to the most up-to date statistics of the U.S. Census Bureau population (2020). Los Angeles is a top U.S destination for international tourists, and travelers have a multiplicity of different needs/expectations when traveling there, allowing for different types of service encounters between experience providers (hotels) and experience receivers (customers).

5.3.2 Measurement

After completing the data collection process, the next decision concerns the choice of an appropriate research approach for operationalizing the focal concepts. Given our aim of contributing to the CR/MR literature, we leverage text mining and other emerging technologies to offer potentially better ways of measuring the compositional elements of MRs and CRs. According to Humphreys and Wang (2017), if the concept is relatively clear, the researcher can use a dictionary to measure the construct through a top-down approach. In principle, a dictionary-based approach entails using a set of rules to count the concepts based on the presence or absence of a particular word. For a dictionary-based analysis, researchers define and then calculate measurements that summarize the textual characteristics that represent the construct. In line with the guidelines provided by Balducci and Marinova (2018) and Berger et al. (2020), we adopt a five-step process to perform dictionary-based analysis to operationalize the focal variable, including (1) text extraction; (2) custom dictionary development; (3) examination of the developed dictionary's reliability and internal and external validity; (4) the production of numeric metrics for the focal variables; and (5) the aggregation of individual-level numeric data to generate a firm-level dataset. **Table 5.2** describes the components of CR and MR, along with our operationalization for these focal variables.

Table 5.2 Operation and Sources of Focal Variables

CR Components		Operationalization
Customers' Emotion	Customer's Positive Emotion	LIWC Dictionary
	Customer's Negative Emotion	LIWC Dictionary
Customer's Rating Behaviors	Customer's Compliments	Custom Dictionary
	Customer's Complaints	Custom Dictionary
	Customers' Referrals	Custom Dictionary
	Customers' Revisit Intentions	Custom Dictionary
	Customers' Rating Scores	Records on Website
MR Components		**Operationalization**
MR Communication Style and the Expression of Similarity between Firm and Focal Guest Reviewer	With/Without MR	Dummy coded
	MR Length	LIWC Dictionary: Words Per Post
	MR Complexity	LIWC Dictionary: Words with more than six letters per sentence
	MR Tone	LIWC Dictionary: Tone
	Similarity Perception	Measure from Herhausen et al. (2019)
MR Content: General	Cognitive Expression	LIWC Dictionary "cogproc"
	Affective Expression	LIWC Dictionary "affect"
MR Content: For Regulating Customers' Positive Emotion	Expressing Thankfulness in General	Custom Dictionary
	Compliments the Customers (Who they are)	Custom Dictionary
	Compliments the Customers' Behaviors (What they did)	Custom Dictionary
	Expression of Sincerity	Custom Dictionary
	Expression of Authenticity	Custom Dictionary
	Expression of Welcoming	Custom Dictionary
	Showing Recommendation of this Guest	Custom Dictionary
MR Content: For Regulating Customers' Negative Emotion	Offering Apology	Custom Dictionary
	Expression of Empathy	Custom Dictionary
	Expression of Explanation	Custom Dictionary
	Showing the Importance of Customers' Reviews	Custom Dictionary
	Showing Improvement/Remedy Action	Custom Dictionary

In our research, we chose the Linguistic Inquiry Word Count 2015 Dictionary to measure customers' positive and negative emotions, managers' communication style, the expression of similarities between firms and the customers who received MR, as well as the cognitive and affective expression in MRs. These variables of interest respond to different word categories in the LIWC dictionary, including a summary of language variables, linguistic dimensions, other grammatical characteristics, affective processes, positive emotion, negative emotion, and cognitive processes. We argue that a dictionary such as the LIWC, which bases its measurement on the underlying linguistic and psychological scales, can provide tighter construct validity. However, no standardized dictionary was available for measuring this study's remaining focal variables that are related to customers' rating behavior and firms' emotional regulation strategies. Thus, it was necessary to create custom dictionaries.

We used the processing program WordState (Peladeau, 2016) to apply the text mining technique to extract words and phrases from the unstructured text data. We separately considered the CRs and the MRs from our TripAdvisor dataset with the aim of developing two custom dictionaries: the CR Dictionary and the MR Dictionary. Then, a list of words and phrases was provided to two experts with doctoral degrees in linguistics to help develop our two customized dictionaries, in which we captured all of the components that could not be measured by the LIWC dictionary, including customers' rating behaviors, firm's positive-emotion regulatory strategies, and firm's negative-emotion regulatory strategies.

We developed a coding scheme for use by the linguistic experts. To produce the initial dictionary, the two linguists separately and independently evaluated and categorized the relevance of each word and phrase, based on the coding schema provided. We followed Berger et al. (2020)'s suggestion to conduct internal dictionary validation. We first assessed the inter-rater consistency and retained words/phrases that were consistently evaluated by the linguistic experts as matching the categories in our coding schema. We then invited a marketing professor to review the words/phrases that were inconsistently judged by the two linguists. The word lists for the categories were updated according to the following rule: if two of the three coders agreed that the word belonged to that category, it should be included; if not, it should be excluded (Humphreys, 2010). We calculated the overall agreement across all the categories, and each exceeded the 0.9 threshold (Rust & Cooil, 1994), leaving us with our final two dictionaries: TripAdvisor CR Dictionary and TripAdvisor MR Dictionary.

To examine the validity of our developed dictionaries, we conducted a correlation analysis, as suggested by Humphreys and Wang (2017), using random subsets of the data and repeating the dictionary-based analyses to produce quantitative sub-datasets upon which we conducted descriptive statistics analysis. The results of the two sub-datasets are congruent. To further ensure external validity, we follow Berger et al. (2020)'s suggestions regarding the prediction of key performance measures (Fossen & Schweidel, 2019). We include variables from the CR/MR Dictionaries in the regression model to predict reviewers' rating scores, the predictive power (R^2 value) is 0.873. We conclude that the predictive validity of the results is established because the text-based variables (customers' rating behaviors and firms' emotion regulating strategies) are linked to the key performance measures. The results show that the particular constructs are theoretically linked to the performance metric of the rating score based on the regression results. For example, the T values of the CR components' coefficients (i.e., compliments, complaints, referral, positive emotion and negative emotion) are 4.14, -5.53, 2.46, 4.48, -7.78, respectively. The T values of the MR components' coefficients (i.e., thankfulness, welcome, sincerity, capability, apology, and admitting mistakes) are 3.56, 2.96, 3.82, -7.05, -5.89 respectively. We argue that the standardized dictionary (LIWC 2015) employed in this study provides support to the internal reliability and external validity (Pennebaker & Francis, 1996; Pennebaker et al., 2015) of the variables the dictionary measures (i.e., positive emotion, negative emotion, tone, style, cognitive expression, affective expression). In addition, text analysis often uses naturally occurring data that are typically of large magnitude and thus tend to have a relatively high degree of external validity (Berger et al., 2020). In summary, we believe that the standardized and developed dictionaries and the numeric metrics of our focal constructs in the current study achieve both internal reliability and validity.

Using LIWC software, we apply a dictionary-based approach to transform unstructured text data into structured numeric data for further analysis. During operation, the LIWC 2015 software accesses our textual dataset one target word at a time. As each target word is processed, the dictionary files (the LIWC Dictionary and the two customized dictionaries) are searched, seeking a match with the target word. If the target word matches a dictionary word, the appropriate word category scales for that target word are incremented. As the original textual datasets are being processed, the counts for various structural composition elements are also incremented. We then receive the final numeric dataset. After converting the text into numeric metrics and assessing the construct validities, we conduct the last data aggregation process for the TripAdvisor dataset with the aim of producing panel datasets for each focal hotel at both daily average and weekly average levels. Other control variables include a hotel's official "star ranking" and its listed price in the TripAdvisor dataset.

5.3.3 Descriptive Statistics and Model-Free Evidence

In **Table 5.3**, we report the basic descriptive statistics for key variables in the datasets, expressed as weekly average datapoints, from the perspective of the individual customer at hotel level.

Table 5.3 Descriptive Statistics of Key Variables

Focal CR Variables					
Major Categorization	**Sub Categorization**	**Min**	**Max**	**Mean**	**S.D.**
Customer Emotion	Positive Emotion	0.00	23.33	6.37	2.59
	Negative Emotion	0.00	7.50	0.76	0.77
Customers' Rating Behavior	Compliments: General CX	0.00	17.24	3.70	1.86
	Compliments: Place/Hotels	0.00	8.57	1.62	1.24
	Compliments: Personal/Service	0.00	7.14	1.39	1.12
	Complaints	0.00	8.51	0.69	0.81
	Referral	0.00	2.86	0.28	0.42
	Revisit Intention	0.00	2.33	0.08	0.22
	Rating Score (from 1-5 Scores)	1.00	5.00	4.08	0.89
Focal MR Variables					
Major Categorization	**Sub Categorization**	**Min**	**Max**	**Mean**	**S.D.**
MR Style	Length	0.00	310.00	56.34	42.52
	Complexity	0.00	40.83	11.36	7.12
	Tone	0.00	99.00	72.46	38.73
Similarity Perception between Manager- Reviewer	CR-MR Linguistic Style Match (%)	0.00	100.00	71.00	37.00
	CR-MR Tone Match (%)	0.00	100.00	74.00	36.00
	Expression of "We"	0.00	15.00	5.09	3.49
	Expression of "He or She"	0.00	2.27	0.06	0.22
	Expression of "They"	0.00	2.38	0.15	0.37
	Expression of "You"	0.00	22.24	6.38	4.06
MR Content	Cognitive Expression	0.00	14.00	4.97	3.50
	Affective Expression	0.00	24.71	9.34	5.71
Regulating Positive Emotions	Expression of Thankfulness	0.00	10.47	1.07	1.25
	Compliments toward Guests Themselves	0.00	2.22	0.11	0.30

	Compliments toward Guests' Actions	0.00	10.11	2.53	2.09
	Expression of Sincerity	0.00	14.55	3.59	2.95
	Expression of Welcoming	0.00	6.90	1.35	1.24
	Recommend Guests to Others	0.00	1.35	0.02	0.11
	Expression of Good Interaction with Guests	0.00	2.48	0.15	0.34
Regulating Negative Emotions	Offering Apology	0.00	2.17	0.12	0.29
	Expression of Empathy	0.00	2.33	0.08	0.27
	Expression of Explanation	0.00	1.27	0.03	0.13
	Expression of the Importance of CR	0.00	2.47	0.17	0.37
	Showing Improvement/Remedy	0.00	2.50	0.36	0.62
	Admitting "Mistakes"	0.00	2.78	0.17	0.42

As presented in **Table 5.3**, we found that customers tend to express more positive emotions than negative emotions in their comments. Similarly, the expression of compliments is higher than that of complaints. Regarding manager's responses on TripAdvisor, the average length of MR is 56 words. The usage of "we" and "you" are much higher than the usage of "he/she" and "they" in MR contents. The expression of affective words is higher than that of cognitive words. The expression of regulating positive emotion/positive CRs is higher than that of regulating negative emotions/negative CR in MRs on TripAdvisor.

In **Figures 5.3-5.4**, we plot the hotels' daily average rating score received at time t against the lagged daily average of customers' rating scores, customers' positive emotions and customers' negative emotions (at time t-1) from the TripAdvisor dataset. In general, there is a positive pattern between the current average rating score and the previous average rating score at the left-hand side of **Figure 5.3**. We also found a slightly positive pattern between average rating scores at time t and average positive emotions at time t-1 at the right-hand side of **Figure 5.3**, suggesting that a positive herding effect may indeed exist in the dataset.

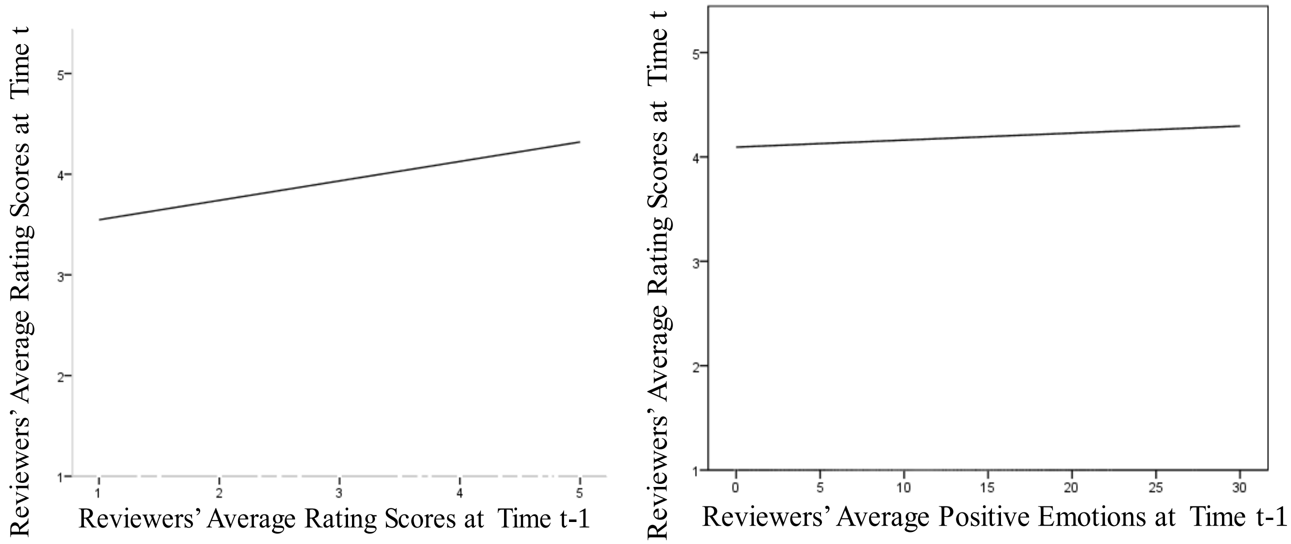


Figure 5.3 Model-Free Evidence of Herding Effects: Positive Patterns between Current Rating Scores and Previous Rating Scores versus Previous Positive Emotions

In **Figure 5.4**, we plot average rating scores at time t against the lagged average negative emotions at time t-1. In general, there is a negative trend between the current rating score (t) and the previous negative emotions (t-1) in CRs, suggesting that negative herding may be prevalent in the data.

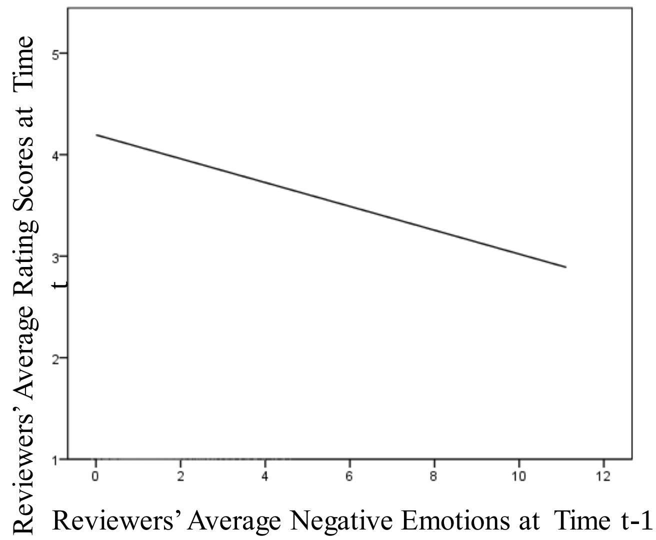


Figure 5.4 Model-Free Evidence of Herding Effects: Negative Pattern between Current Average Rating Scores and Previous Average Negative Emotions

Figure 5.5 tries to illustrate some Online CR-MR Echoverse dynamics. In **Figure 5.5**, we plot the hotels' daily average rating score (received at time t) against the previous daily average of MR's expression of cognitive appraisal and MR's expression of affective infusion (at time t-1). We find that there is a slightly negative pattern between previous MR cognitive expression and the current rating scores in CRs. In contrast, the trend of previous MR's affective expression at time t-1 with later reviewers' rating scores at time t is slightly positive. The relatively imperceptible (non-obvious) patterns prompt us to conduct a more thorough examination in the econometric model described in section 5.3.4.

Similarly, **Figure 5.6** indicates some evidence regarding how a firm's previous regulation strategy at time t-1 toward customers' negative CRs (giving an explanation versus expressing empathy) will influence the rating scores given by future guests later on (at time t). We find that there is a slightly negative trend between the previous expression of empathy in an MR at time t-1 with the current rating scores in CRs at time t. In contrast, the previous MR's expression of explanation at time t-1 exhibits a slightly positive pattern with later reviewers' rating scores in CRs at time t. These results provide some evidence for the spillover effects exerted by MR components on future CRs.

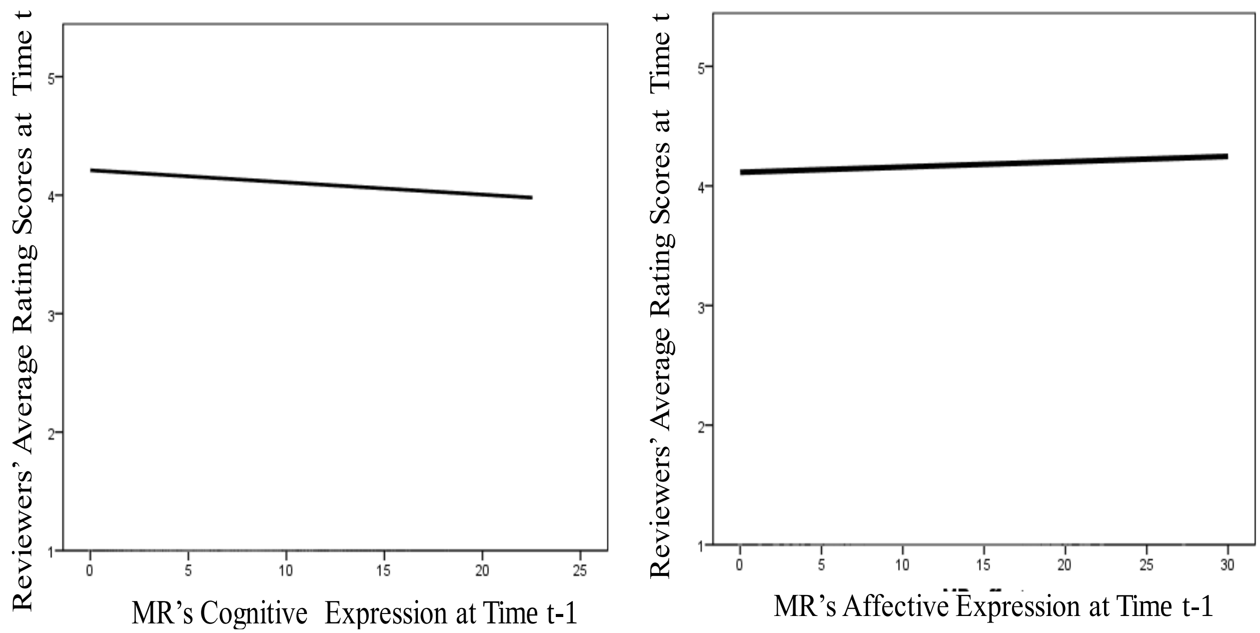


Figure 5.5 Model-Free Evidence of Spillover Effects: Patterns between Previous MR Components (Affective versus Cognitive Expression) and Current Rating Scores

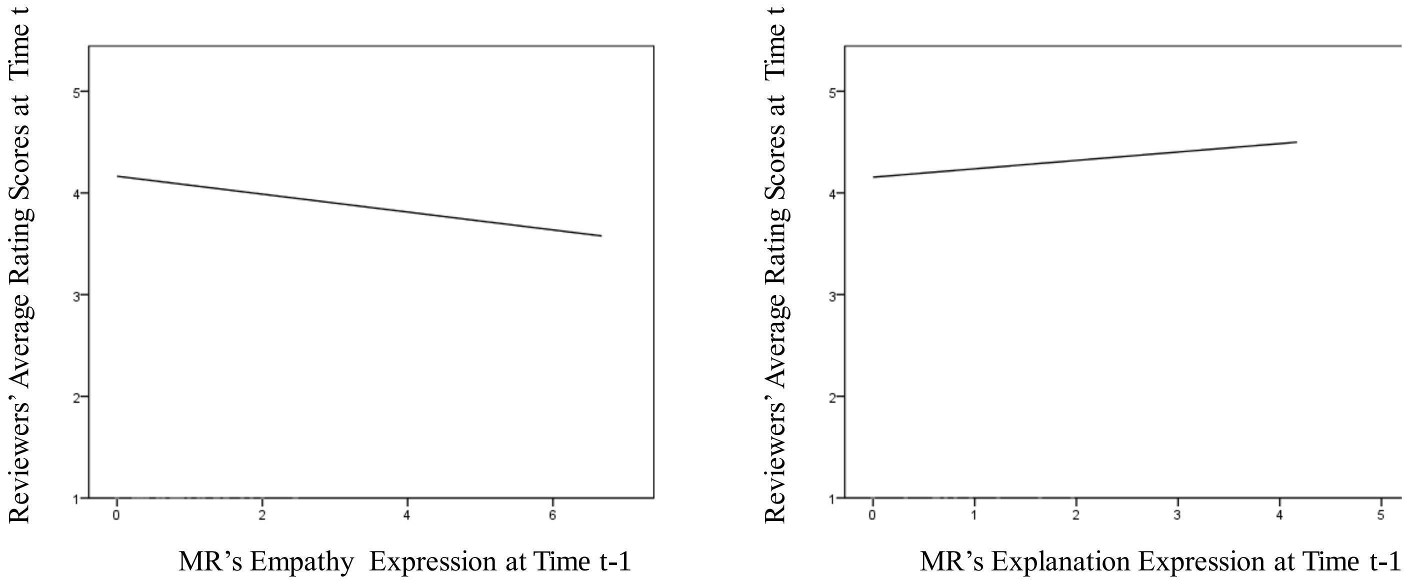


Figure 5.6 Model-Free Evidence of Spillover Effects: Patterns between Previous MR Components (Negative Emotion Regulating Strategies) and Current Rating Scores

On average, **Figures 5.3-5.6** show that dynamic patterns of online CR-MR appear to exist in the data. However, this model-free evidence is correlational at best. We need a robust methodology to disentangle the echoverse dynamics, and to identify the proposed herding effects among the online raters and the spillover effects of MRs on future CRs. In the following section, we present our empirical model. We are interested in the effects of different components of MRs on multiple facets of future customers' emotions and rating performances over time, as well as the herding behaviors among online raters' CRs. Thus, we need to employ a method that allows us to unpack these complex reverberating relationships. We use a VAR model with exogenous control variables (VARX). We focus on the cumulative effects (including short- and long-term accumulative effects) of the different components of MRs over time and compute the elasticities of MR components with impulse response functions (IRFs). This way, we can compare the relative effectiveness of the different components of MRs on our focal CR components (customer positive emotions, negative emotions, compliments, complaints, referral behavior, and revisit intentions).

5.3.4 Modeling Approach

In this subsection, we present the model for the relationships among the variables in the Online CR-MR Echoverse. We use models in the vector autoregressive (VAR) tradition because they enable us to treat all variables as endogenous, which is consistent with the nature of the echoverse. In addition to the binary (with/without) MR variable, almost all variables are (near) continuous; therefore, they can be modeled adequately with a VAR model. We present our modeling specification in the following equation, such that each variable is a linear function of its own past values and the past values of other variables.

$$\begin{bmatrix} CR\_Positive\_Emotion_{i,t} \\ CR\_Negative\_Emotion_{i,t} \\ CR\_Compliments_{i,t} \\ CR\_Complaints_{i,t} \\ CR\_Referral_{i,t} \\ CR\_Revisit\_Intention_{i,t} \\ MR\_With/Without_{i,t} \\ MR\_Length_{i,t} \\ MR\_Style\_Match_{i,t} \\ MR\_Tone\_Match_{i,t} \\ MR\_Expressing\_Thankfulness_{i,t} \\ MR\_Expressing\_Sincerity_{i,t} \\ MR\_Compliments\_Guests_{i,t} \\ MR\_Recommend\_Guests_{i,t} \\ MR\_Welcome\_Guests_{i,t} \\ MR\_Indicating\_Importances_{i,t} \\ MR\_Cognitive\_Expression_{i,t} \\ MR\_Affective\_Expression_{i,t} \\ MR\_Offering\_Explanation_{i,t} \\ MR\_Expressing\_Empathy_{i,t} \\ MR\_Admitting\_Mistakes_{i,t} \\ MR\_Showing\_Improvements_{i,t} \\ MR\_Showing\_Capability_{i,t} \end{bmatrix} = \sum_{j=i}^{p} \Gamma_j \times \begin{bmatrix} CR\_Positive\_Emotion_{i,t-j} \\ CR\_Negative\_Emotion_{i,t-j} \\ CR\_Compliments_{i,t-j} \\ CR\_Complaints_{i,t-j} \\ CR\_Referral_{i,t-j} \\ CR\_Revisit\_Intention_{i,t-j} \\ MR\_With/Without_{i,t-j} \\ MR\_Length_{i,t-j} \\ MR\_Style\_Match_{i,t-j} \\ MR\_Tone\_Match_{i,t-j} \\ MR\_Expressing\_Thankfulness_{i,t-j} \\ MR\_Expressing\_Sincerity_{i,t-j} \\ MR\_Compliments\_Guests_{i,t-j} \\ MR\_Recommend\_Guests_{i,t-j} \\ MR\_Welcome\_Guests_{i,t-j} \\ MR\_Indicating\_Importances_{i,t-j} \\ MR\_Cognitive\_Expression_{i,t-j} \\ MR\_Affective\_Expression_{i,t-j} \\ MR\_Offering\_Explanation_{i,t-j} \\ MR\_Expressing\_Empathy_{i,t-j} \\ MR\_Admitting\_Mistakes_{i,t-j} \\ MR\_Showing\_Improvement_{i,t-j} \\ MR\_Showing\_Capability_{i,t-j} \end{bmatrix} + \left[Control\_Variables\right] + \left[Error\_Terms\right]$$

Where Γ are slope coefficients matrices for endogenous variables, representing the interrelationships between the echoverse variables, allowing for instantaneous (same period) or lagged (later periods) effects between variables. The p value indicates the number of lags, which will be determined using Akaike's information criterion (AIC) and Schwartz's Bayesian information criteria (BIC). More details about the determination of the number of lags will be provided in the next section. We consider two further control variables: hotel "star ranking" and room pricing. These act as hotel fixed effects that account for time-invariant hotel factors. We include two time-unvarying control variables instead of using hotel fixed effects because the control-variable approach is much more parsimonious than hotel fixed effects (there will be 85 dummy variables for hotel identification). Together with the usage of the random sampling procedure, these two control variables account for the hotel fixed effects to estimate the parameter robustly. We estimate the Online CR-MR Echoverse using panel data from the TripAdvisor dataset, which enables us to understand the effects of different components of MRs on the different components of future CRs, This VAR model also enables us to identify the herding effects among raters on TripAdvisor.

5.4 Results

5.4.1 Model Identification

Granger Causality Tests. Before reporting the VAR results, we first discuss the outcomes of the Granger causality tests between variables, with which we test whether the components of MRs and CRs are actually endogenous. There are at least 28 variables in the CR-MR echoverse. Therefore, there are 28x27 possible bivariate effects of one variable on another. Out of these 756 possible effects, 346 show significant Granger causality (significant at 5%) using a Granger causality test for the TripAdvisor weekly dataset. We conclude that each of these echoverse variables is Granger-caused by at least one other variable, and on average, each variable is Granger caused by 13 other variables (more than 50% of the number of total variables). Furthermore, the R-Squares show .09 to .77 for each CR/MR component in the dataset. The R-Squares show reasonable model fit, with more explanatory power for some MR components (i.e., tone, affective expression, cognitive expression, showing sincerity, and welcome). These can be highly explained by the CR-MR echoverse system, expressed by R-square values that are up to

0.77 higher than other CR components (i.e., referral, revisit intention, positive emotion, negative emotions) which exhibit lower R-Square values ranging from 0.09 to 0.29. After the Granger causality test, we proceed to the VAR models to obtain a more complete understanding of the CR-MR echoverse.

5.4.2 Model Estimation

Table 5.4 presents the VAR estimation results from our dataset including the coefficients' significance levels as well as the standard errors of the parameter coefficients. The empirical results use customers' rating scores, emotions (positive and negative), and rating behaviors (compliments, complaints, referrals, revisit intentions) as dependent variables. To aid parsimony, we present only the significant coefficients of independent variables from the lagged CR components and MR components in this table. As presented in **Table 5.4**, the managers' recommendation of the focal reviewer on the first lag has a significant positive relationship with future customers' rating scores. A similar effect is exerted by mentioning interaction with guests in MRs on the third lag. The three MR components that most significantly positively influence wider customers' positive emotions are recommending guests on the first lag, addressing complaints with explanations on the fifth lag, and mentioning interactions with guests on the third lag. Moreover, the previous guest's rating score on the first lag has a similar effect on the positive emotions of wider customers. Regarding wider customers' negative emotions, there are several MR components that will decrease the level of customers' negative emotion, such as using "she" or "he" in MRs on the fourth lag, admitting mistakes on the third lag, and including the manager's name on the sixth lag. The MR components that most significantly increase wider customers' compliments in future CRs include the following: offering explanations and expressing empathy toward customers' complaints and/or unsatisfying experiences in previous CRs (on the fifth and second lags, respectively) as well as mentioning interactions with guests in MRs on the third lag. However, the same MR component of offering explanations on the first and fourth lags exert an opposite effect in that it increases wider customers' complaints in the future. We found that offering explanations on the fourth lag significantly increases both wider customers' negative emotions and complaints in the later CRs. In contrast, offering explanations on the fifth lag significantly increases customers' positive emotions and compliments in the later period. We suggest that firms may need time to fix the problems mentioned by their guests. Thus, complaints made by guests one week and four weeks ago continually influence the current guests' reviews in the current week. When hotel management recognizes that the same complaints have repeatedly appeared in CRs for a month, they may spend a week figuring out the problem. Therefore, the events that generated complaints made five weeks ago are resolved; the fix is observed by the current guests and positively influences their compliments in CRs. To influence current customers' referrals, the three most significant MR components are expressing compliments toward guests at the fourth lag and expressing empathic feelings with regard to previous guests' unsatisfying experiences on the second and third lags. Finally, wider customers' revisit intentions in current CRs can be significantly explained by the MRs on the sixth lag that express recommendations for the staying guests.

Interestingly, **Table 5.4** demonstrates backfire effects that warrant attention. For example, offering explanations in MRs on the fourth lag exerts significant negative associations with wider customers' rating scores, positive emotions, and compliments in current CRs. Similarly, the same MR component has positive relationships with customers' negative emotions and complaints in current CRs. Another MR component that exerts backfire effects on desirable customer emotions and the rating score is the provision of remedies on the fifth lag, which is negatively associated with rating scores and positive emotions, and positively associated with negative emotions in wider customers' current CRs. We suggest that this may come about when firms suggest remedies for the unsatisfying experience of the previous guests from five weeks ago. If the proposed remedies are observed to have been not delivered by the "current" guests, then this failure to follow through will significantly decrease current guests' rating score and positive emotions in their CRs in the current week.

Generally, the results in **Table 5.4** suggest that to positively influence later customers' rating scores, positive emotions, referrals, and revisit intentions, MRs should include components such as expressing good interactions, using empathic words, and offering explanations for the issues that cause dissatisfaction in guests.

Table 5.4 Model Estimate Results

Left Hand Side Variables at Time t	Significantly Positive Effects Exerted by Right Hand Side Variables at Time t-j	Coefficients	Significantly Negative Effects Exerted by Right Hand Side Variables at time t-j	Coefficients
CR_ Reviewers' Rating Scores	CR_ Reviewer Rating $_{t-1}$	0.11***	CR_ Positive Emotion $_{t-1}$	-0.02**
	CR_ Reviewer Rating $_{t-3}$	0.08**	CR_ Compliments of Hotel/Facilities $_{t-4}$	-0.04**
	CR Reviewer Rating $_{t-4}$	0.12***	MR_ Length $_{t-1}$	-0.002**
	CR Reviewer Rating $_{t-5}$	0.11***	MR_ Tone $_{t-3}$	-0.01**
	CR_ Reviewer Rating $_{t-7}$	0.13***	MR_ Affective Expression $_{t-1}$	-0.03**
	CR_ Compliments of Personal Service $_{t-1}$	0.03**	MR_ Compliments of Guests' Behaviors $_{t-3}$	-0.03**
	CR__ Referral $_{t-3}$	0.08**	MR_ Interaction $_{t-2}$	-0.13**
	MR_ Affective Expression $_{t-3}$	0.03**	MR_ Admitting Mistakes $_{t-6}$	-0.10**
	MR_ Expression "Welcome" $_{t-4}$	0.06**	MR_ Offering Explanation $_{t-1}$	-0.16**
	MR_ Recommend Guests $_{t-1}$	0.27**	**MR_ Offering Explanation $_{t-4}$**	-0.28***
	MR_ Expression of Good Interaction $_{t-3}$	0.20***	MR_ Showing Improvements $_{t-7}$	-0.10**
	MR_ Expression of firm's Capabilities $_{t-4}$	0.03**	**MR_ Providing Remedy $_{t-5}$**	-0.22***
	MR_ Expression of Manager's Names $_{t-6}$	0.12**		
CR_ Positive Emotion	CR_ Reviewer Rating $_{t-1}$	0.36***	CR_ Compliments of Hotel/Facilities $_{t-4}$	-0.12**
	CR_ Positive Emotion $_{t-2}$	0.07**	CR_ Compliments of Hotel/Facilities $_{t-6}$	-0.10**
	CR_ Positive Emotion $_{t-6}$	0.08**	CR_ Referral $_{t-6}$	-0.26**
	MR_ Recommend Guests $_{t-1}$	0.87**	MR_ Tone $_{t-4}$	-0.02**
	MR_ Expression of Good Interaction $_{t-3}$	0.71***	MR_ Mention of "She/He" $_{t-6}$	-0.48**
	MR_ Offering Explanation $_{t-5}$	0.73**	MR_ Mention of "You" $_{t-5}$	-0.09**
			MR_ Compliments of Guests Themselves $_{t-5}$	-0.42**
			MR_ Offering Explanation $_{t-4}$	-0.60**
			MR_ Offering Remedies $_{t-5}$	-0.49**
CR_ Negative Emotion	CR_ Positive Emotion $_{t-1}$	0.02**	CR_ Reviewers' Ratings $_{t-1}$	-0.06**
	CR_ Negative Emotion $_{t-2}$	0.09***	CR_ Complaints $_{t-7}$	-0.05**
	MR_ Tone $_{t-6}$	0.01**	MR_ Expression of "She/He" $_{t-4}$	-0.13**
	MR_ Affective Expression $_{t-1}$	0.03**	MR_ Expression of "Welcome" $_{t-4}$	-0.05**
	MR_ Offering Explanation $_{t-4}$	0.17**	MR_ Admitting Mistakes $_{t-3}$	-0.08**
	MR_ Showing Improvement $_{t-3}$	0.07**	MR_ Expressing Manager's Names $_{t-6}$	-0.09**

Left Hand Side Variables at Time t	Significantly Positive Effects Exerted by Right Hand Side Variables at Time t-j	Coefficients	Significantly Negative Effects Exerted by Right Hand Side Variables at time t-j	Coefficients
	MR_ Offering Remedies $_{t-5}$	**0.22*****		
CR_ Compliments	CR_ Reviewers' Rating $_{t-1}$	0.24***	CR_ Referral $_{t-6}$	-0.18**
	CR_ Negative Emotion $_{t-1}$	0.14**	MR_ Tone $_{t-6}$	-0.02**
	MR_ Expression of Good Interaction $_{t-3}$	**0.35****	MR_ Expression of "She/He" $_{t-5}$	-0.30**
	MR_ Offer Explanations $_{t-5}$	**0.59*****	MR_ Expression of "Welcome" $_{t-1}$	-0.14**
	MR_ Expressing Empathy $_{t-2}$	0.37**	**MR_ Offering Explanations $_{t-4}$**	**-0.48****
CR_ Complains			CR_ Reviewers' Rating $_{t-1}$	-0.09***
	CR_ Compliments of Hotels/Facilities $_{t-6}$	0.03**	CR_ Complaints $_{t-6}$	-0.06**
	CR_ Complaints $_{t-1}$	0.08***	MR_ Logistic Style Match $_{t-6}$	-0.01**
	CR_ Complaints $_{t-2}$	0.05**	MR_ Expression of "They" $_{t-4}$	-0.10**
	CR_ Complaints $_{t-3}$	0.05**	MR_ Cognitive Expression $_{t-1}$	-0.03***
	CR_ Complaints $_{t-4}$	0.05**	**MR_ Recommend Guests $_{t-1}$**	**-0.26****
	CR_ Referral $_{t-2}$	0.11***	**MR_ Expression of Interaction $_{t-1}$**	**-0.22*****
	MR_ Tone$_{t-6}$	0.01***	MR_ Showing Capabilities $_{t-4}$	-0.03**
	MR_ Cognitive Expression $_{t-2}$	0.02**	MR_ Expressing Manager's Names $_{t-3}$	-0.10**
	MR_ Showing Capabilities $_{t-3}$	0.03**	MR_ Expressing Manager's Names $_{t-6}$	-0.13***
	MR_ Expressing Manager's Names $_{t-5}$	0.10**	MR_ Showing Remedies $_{t-4}$	-0.12**
	MR_ Offering Explanations $_{t-1}$	**0.22****		
	MR_ Offering Explanations $_{t-4}$	**0.28*****		
CR_ Referral	CR_ Compliments of Hotels/Facilities $_{t-7}$	0.02**	CR_ Referral $_{t-6}$	-0.06**
	MR_ Length t-4	0.001**	MR_ Expression of "They" $_{t-7}$	-0.07**
	MR_ Expression of "We" $_{t-4}$	0.02**	MR_ Expression of "You" $_{t-1}$	-0.02**
	MR_ Expression of "They" $_{t-5}$	0.07**	MR_ Recommend Guests $_{t-7}$	-0.16**
	MR_ Compliments of Guests Themselves $_{t-4}$	0.11***	MR_ Expression of Capabilities$_{t-7}$	-0.01**
	MR_ Expressing Empathy$_{t-1}$	0.09**		
	MR_ Expressing Empathy $_{t-2}$	0.10**		
	MR_ Expressing Empathy $_{t-3}$	0.11**		
	CR_ Positive Emotion $_{t-2}$	0.01**	CR_ Referral $_{t-1}$	-0.03**

Left Hand Side Variables at Time t	**Significantly Positive Effects Exerted by** Right Hand Side Variables at Time t-j	Coefficients	**Significantly Negative Effects Exerted by** Right Hand Side Variables at time t-j	Coefficients
CR_ Revisit	CR_ Compliments of CX $_{t-4}$	0.01***	MR_ Tone $_{t-1}$	-0.002**
	MR_ Linguist Style Match$_{t-1}$	0.005**	MR_ Tone $_{t-3}$	-0.002**
	MR_ Cognitive Expression $_{t-2}$	0.01***	MR_ Linguist Style Match$_{t-7}$	-0.004**
	MR_ Cognitive Expression $_{t-7}$	0.01**	MR_ Expression of “We” $_{t-2}$	-0.01**
	MR_ Expressing Sincerity $_{t-2}$	0.01**	MR_ Expression of: You” $_{t-5}$	-0.01**
	MR_ Recommend Guests $_{t-6}$	0.16***	MR_ Cognitive Expression $_{t-1}$	-0.01**
	MR_ Expressing Positive Interaction $_{t-7}$	0.06**	MR_ Cognitive Expression $_{t-4}$	-0.01**
			MR_ Affective Expression $_{t-1}$	-0.01**
			MR_ Expression of “Welcome” $_{t-2}$	-0.02**
			MR_ Offering Explanations $_{t-2}$	-0.06**
			MR_ Showing Improvements $_{t-5}$	-0.03**

Our results demonstrate that previous MRs offering explanations 5 weeks before the focal customers' posting week will positive influence those customers' rating scores and positive emotions; however one week later, the same MR component (which is given 4 weeks prior to the focal customers' posting week) exerts negative effects on those customers' rating scores and positive emotions and triggers their negative emotions. We can integrate these findings with those related to another MR component: offering remedies. When remedies are offered 5 weeks prior to the focal customers' posting week, this MR component will exert negative effects on those customers' rating scores and positive emotions, and increase their negative emotions. We explain these findings as follows. Potential customers observe the reviews of previous customers and the manager's responses to those reviews around 5 weeks before they are due to travel. These potential customers might observe from the CRs that previous guests had enjoyed less than satisfactory experiences in the hotel but that the manager had offered explanations and remedies for these issues. If these later guests found that the sources of dissatisfaction had been removed or did not recur by the time of their own visits they will interpret this as evidence that the hotel management listens to the guests' voices and takes action accordingly. Thus, in this situation, offering explanations in MRs for guests' unsatisfactory experiences will positively influence future customers' rating behaviors and emotions.

However, what if the hotel were to put forward an explanation or remedy in the MR but does not act upon it? This might explain the negative impact of explanations offered in MRs four weeks prior to the focal customers' CRs. If the focal customers find that the issue remains unresolved during their own stay in the hotel four weeks after the issue was identified by previous guests, then these MR components, which offered explanations 4 weeks ago and promised to provide remedies 5 weeks ago, would rebound on the focal customers' rating score, positive emotions, and negative emotions.

We conclude from our results that later customers will be influenced during a relatively short time span by the components of previous MRs toward earlier customers' positive experiences, including the recommendation of guests (one week prior to the later customers' CR posting week) and expression of good interactions between firms and customers (three weeks prior to the later customers' CR posting week). On the other hand, later customers will be impacted by a relatively longer time span between previous MR components that respond to earlier customers' complaints, including offering explanations and providing remedies (5 weeks prior to the later customers' posting week).

We thus argue that that there is a time-frame effect for how different MR components influence future CRs. Our findings demonstrate that when later customers post their CRs, they will be influenced by the contents of MRs that respond to a previous customer's good experience going back around 1-3 weeks prior to their own posting week. However, MRs that respond to an earlier customer's bad experience will exert longer term effects (going back 4-5 weeks prior to their own CR posting week). Specifically, management explanations in response to CRs that describe customer dissatisfaction exert double-edged effects on later customers' rating scores and emotion regulation.

Another finding needs to be highlighted concerns the trade-offs between the MR strategies of (1) complimenting guests and (2) recommending guests in regulating future customers' positive emotions and referral behaviors.

As presented in **Table 5.4**, recommending guests in MRs will positively influence later customers' positive emotions while negatively influencing their referral behaviors. Specially, the positive emotions of later customers are triggered by firms' recommendations of previous guests at t-1(week). In contrast, these recommendations negatively influence the referrals of later customers at t-7(weeks). Thus, firms should pay attention to their strategic usage of recommending guests in their MRs, which will exert positive effects in the short run (one week afterwards) on future customers' positive emotions but generate backfire effects in the long run (7 weeks afterwards) on later customers' referral behaviors.

The other MR component that has trade-off effects on future customers' positive emotion and referring behaviors is the complimenting of earlier guests. Based on the results in **Table 5.4**, firms that leverage the complimenting of guests in their MRs at t-5 (weeks) will negatively influence later customers' positive emotions. However, complimenting guests in previous MRs at t-4 (weeks) will positively influence later customers' referral behaviors. This positive causal result echoes the perspective of the reciprocal relationship identified in the relationship management literature. In offline contexts, people generally recognize that reciprocal relationships evoke exchange norms, which bind them to specific actions (Dahl, Honea, & Machanda, 2005). Research has shown that reciprocity implies responsibility (Nass & Yen, 2010). Experiments reveal that when even complete strangers interact online for a mere five minutes about inconsequential issues, they feel a sense of responsibility to reciprocate (Nass & Yen, 2010). Therefore, we argue that managers' compliments about earlier guests in MRs will imply a sense of reciprocity in future guests. This highlights a key point about social behaviors, leading to the temporal reciprocal effect regarding hotel managers' compliments to earlier guests and future guests' referral of the focal hotel. **Table 5.5** summarizes some important findings from **Table 5.4**, listing the MR components that are most critical to achieving managerial goals and the MR components that might exert backfire effects on the managerial objectives of increasing customers' rating scores, positive emotions, and compliments while decreasing their negative emotions and complaints in future CRs.

Table 5.5 Effective Combinations of MR Components to Achieve Managerial Goals

Managerial Goals	Effective Combinations of MR Components as CR Managerial Strategy	Backfires: MR Components Exerting Opposite Effects on Desired Managerial Goals
1. Increasing Customer's Positive Emotion	· Recommending Guests $_{t-1}$ · Expression of Good Interaction $_{t-3}$ · Offering Explanations $_{t-5}$	· Offering Explanation $_{t-4}$ · Providing Remedies $_{t-5}$
2. Decreasing Customers' Negative Emotion	· Expression of "She/He" $_{t-4}$	· Offering Explanation $_{t-4}$ · Providing Remedies $_{t-5}$
3. Increasing Customers' Rating Scores	· Recommending Guests $_{t-1}$ · Expression of Good Interaction $_{t-3}$	· Offering Explanation $_{t-4}$ · Providing Remedies $_{t-5}$
4. Increasing Customers' Compliments	· Expression of Good Interaction $_{t-3}$ · Offering Explanations $_{t-5}$	· Expression of "She/He" $_{t-5}$ · Offering Explanations $_{t-4}$
5. Decreasing Customers' Complaints	· Recommending Guests $_{t-1}$ · Expression of Good Interaction $_{t-1}$	· Offering Explanations $_{t-1}$ · Offering Explanations $_{t-4}$

5.4.3 Quantifying the Over-Time Impacts of Significant MR Components on Future CRs

Through generalized impulse response functions (IRFs), we can summarize the effects between the endogenous variables and show the full dynamic impact of a standard deviation shock in one variable on the other variables (Hewett et al., 2016; Pesaran & Shin, 1998). We argue that the main interest of the VAR models lies in the net results of all the modeled MR components and the consequent reactions of the focal CR components (customers' emotions and their rating behaviors), which can be derived from the estimated coefficients through the associated IRFs (Bronnenberg et al., 2000; Litterman, 1984). Therefore, we operationalize a change to a focal MR component as a shock to the affected CR series (i.e., positive emotions, referrals, rating scores). An impulse response function then tracks the impact of the shock to the variables in the Online CR-MR Echoverse during the shock and for each period thereafter.

Table 5.6 presents how these IRFs stimulate the over-time impact of a change in the MR components on our focal CR variables in the full dynamic system. We present the IRF results at 4 weeks, 8 weeks, and 12 weeks for parsimonious and practical purposes. We argue that the 4-week period can be seen as the accumulated influences of specific MR components on specific CR components over one month, defined as the short-run accumulated effects. The 8-week period can be viewed as the two-month accumulated effects while the 12-week period can be interpreted as the accumulated effects exerted by specific MR components on specific future CR components over a three-month period. **Table 5.6** presents the results of IRF for customers from the TripAdvisor website related to the accumulated response of focal CR components (rating scores, positive emotions, negative emotions, referrals, and revisit intentions) toward the MR components.

Table 5.6 Results of Impulse Response Function (IRF)

One Unit (One S.D.) of Change (Increase) from MR Components	Accumulated Influences on Rating Scores			Accumulated Influences on Positive Emotion			Accumulated Influences on Negative Emotion			Accumulated Influences on Referral Behavior			Accumulated Influences on Revisit Intention		
	Influential Periods (weeks)			Influential Periods (weeks)			Influential Periods (weeks)			Influential Periods (weeks)			Influential Periods (weeks)		
	4	**8**	**12**	**4**	**8**	**12**	**4**	**8**	**12**	**4**	**8**	**12**	**4**	**8**	**12**
Length	-0.03	-0.07	-0.11	-0.02	-0.05	-0.09	0.00	0.03	0.07	-0.02	-0.01	-0.00	0.00	-0.00	-0.03
Tone	0.02	0.03	0.02	0.08	-0.01	0.00	-0.03	-0.03	-0.03	-0.00	-0.02	-0.03	0.00	0.03	0.02
Logistic Style Match	0.04	0.05	0.08	-0.02	0.02	0.05	-0.01	-0.07	-0.08	0.01	0.00	-0.00	0.02	0.02	0.04
Expression of “We”	-0.00	-0.06	-0.11	-0.02	-0.12	-0.17	0.05	0.05	0.08	-0.01	0.00	0.02	-0.02	-0.05	-0.00
Expression of “They”	-0.01	-0.06	-0.10	0.03	-0.13	-0.26	0.01	0.02	0.04	0.01	-0.00	-0.01	-0.01	-0.00	-0.01
Expression of “She/He”	0.01	-0.00	-0.04	0.04	-0.12	-0.22	-0.01	-0.04	-0.03	-0.01	-0.02	-0.02	0.00	0.01	0.01
Expression of “You”	**0.03**	**0.07**	**0.10**	0.00	-0.11	-0.17	-0.03	-0.04	-0.05	-0.03	-0.01	-0.01	0.01	0.01	0.03
Cognitive Expression	-0.01	0.04	0.09	-0.04	-0.09	-0.03	-0.00	-0.03	-0.04	-0.01	0.00	0.01	0.00	-0.01	-0.01
Affective Expression	0.01	0.03	0.09	**-0.07**	**0.06**	**0.18**	0.06	0.07	0.06	-0.00	-0.02	-0.02	0.01	0.02	0.01
Expressing Thankfulness	0.00	0.01	0.01	-0.06	-0.18	-0.30	-0.00	-0.02	0.01	-0.00	-0.02	-0.02	-0.00	-0.01	0.00
Expressing Sincerity	**0.05**	**0.07**	**0.11**	**-0.05**	**0.02**	**0.15**	-0.02	-0.01	-0.03	0.02	0.03	0.03	0.00	0.01	0.05
Expressing Welcome	-0.01	0.04	0.08	-0.02	0.05	0.08	0.02	0.01	0.00	-0.00	-0.00	-0.00	-0.03	-0.04	-0.01
Expressing Interaction	**0.05**	**0.15**	**0.26**	**0.13**	**0.32**	**0.58**	**-0.01**	**-0.06**	**-0.12**	0.03	0.03	0.04	0.01	0.03	0.05
Recommend Guests	**0.04**	**0.09**	**0.11**	**0.24**	**0.57**	**0.78**	**-0.05**	**-0.15**	**-0.21**	0.02	0.01	0.02	-0.00	0.01	0.04
Compliments of Guests	-0.02	-0.04	-0.07	0.13	0.07	0.09	0.06	0.05	0.05	0.01	0.05	0.07	-0.00	-0.02	-0.02
Compliments of Guest’s Action	-0.04	-0.04	-0.08	-0.04	-0.17	-0.18	0.02	0.04	0.06	0.01	-0.00	-0.01	-0.01	-0.01	-0.04
Offering Apology	0.02	0.03	0.03	0.05	0.10	0.08	-0.01	-0.06	-0.07	0.03	0.02	0.03	0.01	0.00	0.02
Offering Explanation	-0.05	-0.13	-0.18	-0.14	-0.13	-0.18	0.02	0.07	0.09	-0.03	-0.07	-0.06	-0.03	-0.06	-0.05
Expressing Empathy	0.03	0.05	0.06	**0.06**	**0.02**	**0.10**	-0.03	0.01	0.01	**0.07**	**0.08**	**0.10**	-0.00	-0.00	0.03
Showing Improvements	0.02	0.01	0.01	**0.01**	**0.10**	**0.11**	-0.00	-0.02	-0.06	-0.02	-0.03	-0.03	0.01	0.01	0.02
Offering Remedies	0.00	-0.06	-0.11	-0.05	-0.17	-0.24	-0.04	0.05	0.08	-0.02	0.01	0.01	-0.02	-0.01	0.00
Showing CR’s Importance	0.01	0.04	0.07	-0.02	-0.04	-0.01	0.00	-0.02	-0.02	0.01	-0.02	-0.04	0.00	0.01	0.01

As presented in **Table 5.6**, the first three MR components that will cause an accumulated response in over 10% of wider customers' rating scores are expressions of interaction (26%), expressions of sincerity (11%), and recommendations of guests (11%) over the 12 week period. The first five MR components that will cause a positively accumulated response in the positive emotions of over 10% of wider customers are recommendations of guests (78%), expressions of interaction (58%), affective expressions in MRs (18%), expressions of sincerity (15%) as well as showing improvements (11%), again over a 12 week period. There are two MR components that will cause a decrease in accumulated response of over 10% for wider customers' negative emotions: recommendations of guests (-21%) and expressions of interaction (-12%).

In contrast, some backfire effects exist that will cause rating scores to cumulatively decrease by over 10% in the 12^{th} week, such as offering explanations in MRs (-18%), offering remedies for unsatisfactory experiences (-11%), MR length (-11%) and using "we" in MRs (-11%). There are seven MR components that will negatively impact by over 10% the accumulated responses of positive emotion in the 12^{th} period, including using "they" in MRs (-26%), offering remedies in MRs (-24%), using "she or he" in MRs (-22%), offering explanations for unsatisfactory experiences (-18%), complimenting guests' behaviors/actions (-18%), using "we" (-17%), and using "you" in MRs (-17%).

Generally, the MR components that will most effectively increase future customers' rating scores in the short run (within 4 weeks, around one month) is the expression of sincerity and good interactions with guests. In the long run (within 12 weeks, around 3 months), the most effective MR component is the expression of good interactions with guests. To generate future customers' positive emotions and mitigate their negative emotions, the effective short-run (4 week) and long-run (12 week) strategies are the same: expressing good interactions and recommending guests in MRs. To encourage future customers' referral behavior, expressing empathy in the MRs is effective at exerting short-run (4 weeks) and long-run (12 weeks) effects on future CRs. To increase future customers' revisit intentions as expressed in their CRs, the expression of good interactions with guests is suggested to be a good short-term and long-term strategy.

The following two figures (**Figures 5.7** and **5.8**) visualize the increasing and decreasing patterns of customers' rating scores in the long run, in response to selected MR components. As presented in **Figure 5.7**, the MR component that is most effective at positively increasing rating scores in the long run (12 weeks) is the expression of interaction. However, the component that must be avoided in MRs is the proffering of explanations, which triggers a downward pattern for rating scores in the long run, as can be seen in **Figure 5.8**.

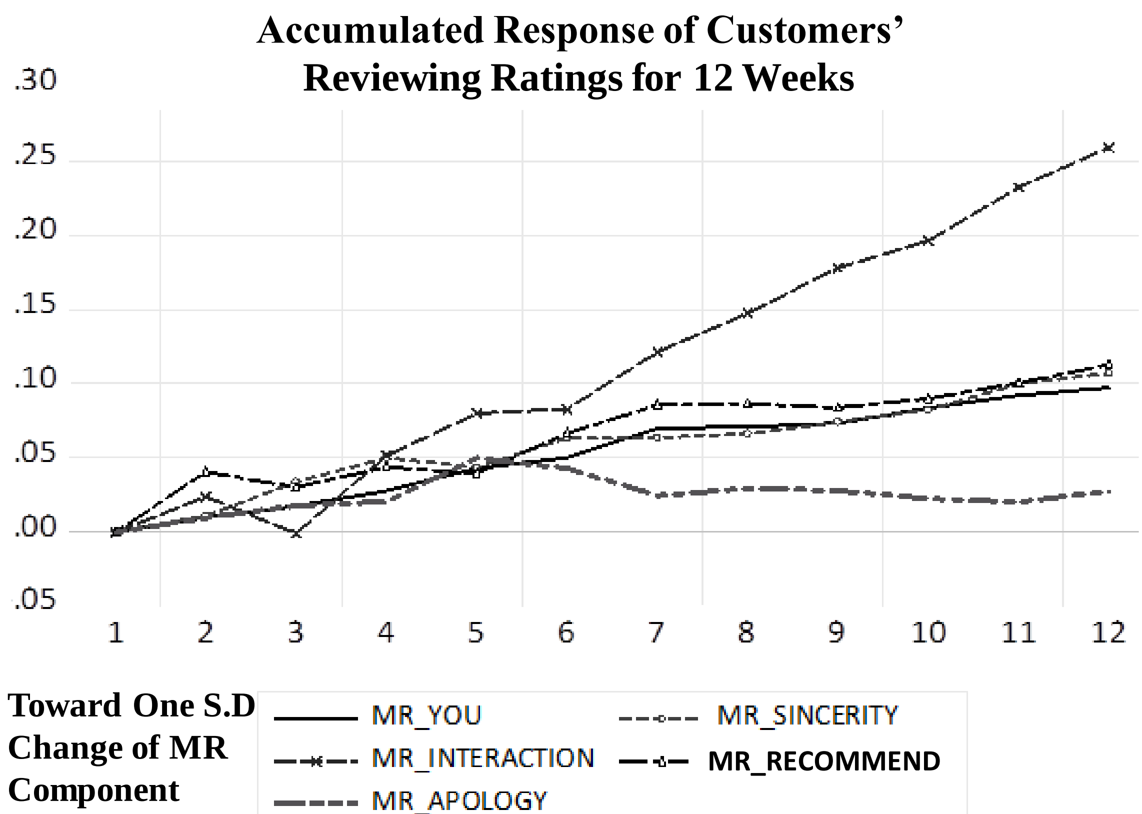


Figure 5.7 Positively Accumulated Response of Rating Scores toward MR Components

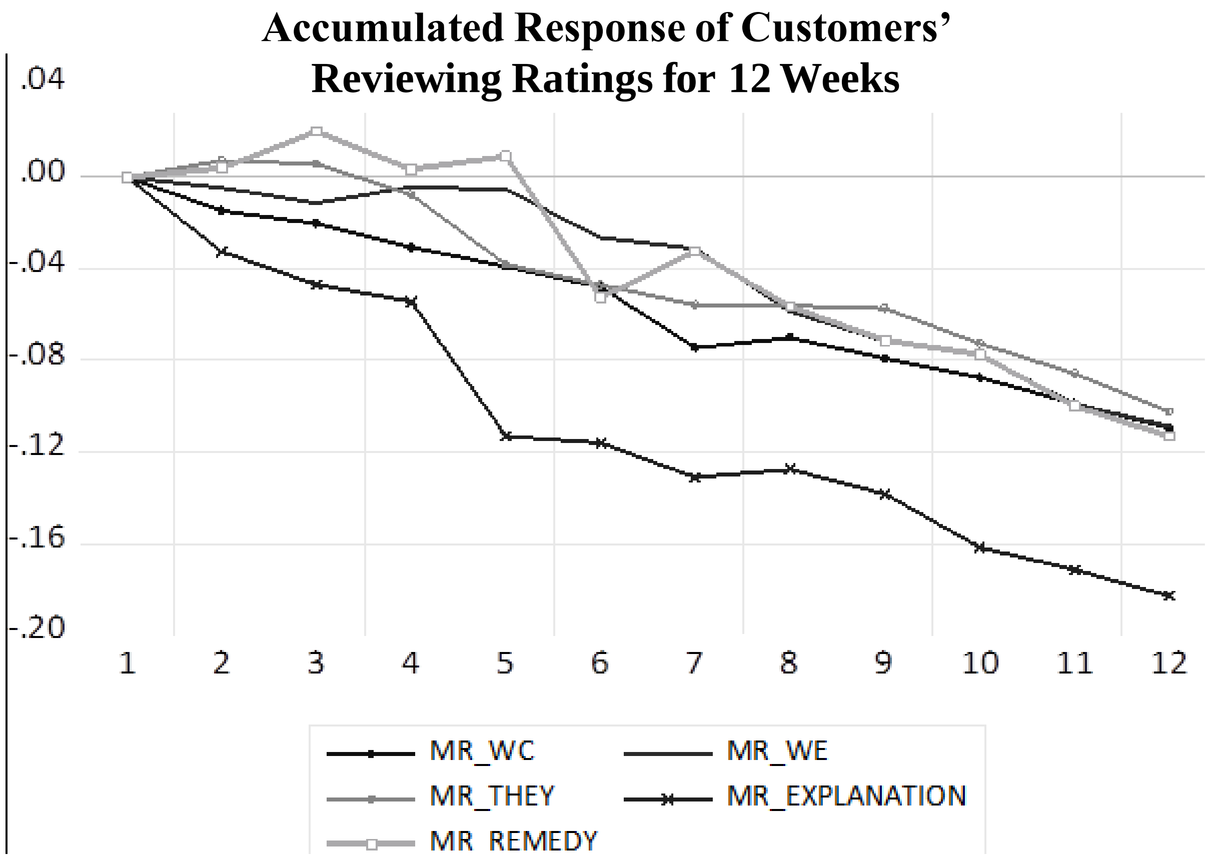


Figure 5.8 Negatively Accumulated Response of Rating Scores to MR Components

After leveraging the impulse response function (IRF) to track the effect of an MR component shock to the full CR-MR echoverse, we employ the forecast error variance decomposition (FEVD) approach to gain a deeper understanding of the herding effects among customers on the TripAdvisor website. FEVD can help to reveal how the forecast error variance in one variable (e.g., customers' rating score) can be explained by its own past shocks and the variance from the shocks of all the other endogenous variables. Analogous to a dynamic R^2, FEVD enables the identification of the relative importance of each variable's contribution to the variation in the performance variable.

In the FEVD approach, an initial shock is allowed to affect all other endogenous variables instantaneously. To evaluate the accuracy of the estimates, Nijs et al. (2007)

obtain standard errors using Monte Carlo simulations (see Benkwitz et al., 2001). The FEVD always sums up to 100%, typically with the past performance of the focal variable explaining most of its variance. **Table 5.6** shows the percentage of variance explained by the focal CR components (rating score, positive emotions, negative emotions, referrals, and revisit intentions) as a means of understanding the herding behaviors among customers. In this paper, the % of "inertia" is of special interest since it represents the herding effects among CR components.

As presented in **Table 5.7**, the rating score can be best explained by its own past shocks. It is reasonable to interpret that the forecast error variance in future customers' rating scores can be best explained by the shock from previous customers' rating scores. In other words, the rating score of previous customers is the most important cause of the variation in the current customers' rating score. The other two rating performance variables that can best be explained by their own pasts are customers' referrals and their revisit intentions. Moreover, we can gain another perspective regarding the long-term effects (within 12 weeks) of MR components on these CR focal components by concentrating only on the percentage of the performance that is explained by the MR components. The bottom line of **Table 5.7** shows how MR components improve around 8% of FEVD that is not explained by the focal CR components' own pasts. In other words, previous MR components contribute 8.22% to explain the variance of the later rating score, 7.08% to explain the variance of positive emotion, 7.07% to explain later customers' negative emotion, 7.01% to explain later customers' referral behavior, and 8.36% to explain later customers' revisit intentions.

Table 5.7 Results of Forecast Error Variance Decomposition (FEVD) for Herding Behaviors

Period (Week)	S.E. of Rating Score	% of variance of rating score explained by itself	S.E. of Positive Emotion	% of variance of positive emotion explained by itself	S.E. of Negative Emotion	% of variance of negative emotion explained by itself	S.E. of Referral	% of variance of referral explained by itself	S.E. of Revisit Intention	% of variance of revisit intention explained by itself
1	0.82	100%	2.74	80.11%	0.81	73.21%	0.49	97.23%	0.28	99.22%
2	0.83	98.26%	2.77	78.49%	0.81	72.05%	0.49	95.98%	0.28	97.99%
3	0.84	97.66%	2.79	77.68%	0.82	71.64%	0.49	94.63%	0.28	95.72%
4	0.85	96.02%	2.81	76.29%	0.82	70.56%	0.50	93.42%	0.29	94.61%
5	0.86	94.19%	2.84	75.05%	0.83	69.48%	0.50	92.05%	0.29	92.68%
6	0.88	93.21%	2.88	73.34%	0.84	68.09%	0.50	91.29%	0.29	91.32%
7	0.89	91.92%	2.91	71.96%	0.85	66.75%	0.51	90.48%	0.29	89.87%
8	0.90	91.24%	2.94	70.90%	0.85	65.79%	0.51	89.37%	0.30	88.65%
9	0.91	90.98%	2.95	70.50%	0.86	65.60%	0.51	89.22%	0.30	88.46%
10	0.92	90.59%	2.96	70.06%	0.86	65.31%	0.51	89.05%	0.30	88.26%
11	0.92	90.05%	2.97	69.59%	0.86	65.01%	0.51	88.95%	0.30	88.08%
12	0.93	89.65%	2.98	69.17%	0.86	64.78%	0.51	88.83%	0.30	87.91%
% of Variance Explained by All other MR Components in the 12th period										
		8.22%		**7.08%**		**7.07%**		**7.01%**		**8.36%**

Table 5.7 shows that there are noticeable herding behaviors among customers' rating behaviors. Specially, future customers' rating scores, referrals, and revisit intentions can be largely influenced by previous customers' rating scores, referrals, and revisit intentions. Moreover, **Table 5.8** shows the multiple sources of herding effects. Regarding customers' positive and negative emotions, which are partly influenced by previous customers' emotions, there is another CR component, rating score, that can explain up to 21.85% of the variances in positive emotion and up to 25.92% of the variances in negative emotion (in the 12th week for both).

Table 5.9 decomposes the herding effects among customers' complimentary behaviors into the influences exerted by the previous customers' compliments and the other focal CR components, including positive emotion (30.89% for compliments toward the CX, 12.36% for compliments toward people) and rating score (14.45% for compliments toward the CX, 9.29% for compliments toward people). **Tables 5.8-5.9** prove that customers adjust their emotions and rating behaviors in line with the online rating information of the crowd. That is, to conform to the crowd's opinion, customers' emotions and rating behaviors are positively related to previous customers' emotions and rating behaviors.

Integrating the results from **Table 5.8** and **Table 5.9**, we conclude that previous rating score is the most critical source of customers' herding behaviors. Previous rating scores will exert herding effects not only on the later customers' rating scores, but also on later customers' emotions. Through considering the herding behaviors among all the CRs simultaneously, we find that MRs still have explanatory power of between 7%-8% to explain variances in customers' emotions and rating scores.

Table 5.8 Results of Forecast Error Variance Decomposition (FEVD): The Multiple Sources of Herding Effects of Customers' Emotions

	% of Variance of Positive Emotion Explained by itself and Rating Score in CRs		% of Variance of Negative Emotion Explained by itself and Rating Score in CRs	
Period (Weeks)	**(1) Positive Emotion**	**(2) Rating Score**	**(1) Negative Emotion**	**(2) Rating Score**
1	80.11%	19.89%	73.21%	26.12 %
2	78.49%	20.22%	72.05%	25.96 %
3	77.68%	20.34%	71.64 %	25.65 %
4	76.29%	20.40%	70.56 %	25.53 %
5	75.05%	20.59%	69.48%	25.53 %
6	73.34%	20.69%	68.09 %	25.58 %
7	71.96%	20.79%	66.75 %	25.53 %
8	70.90%	21.11%	65.79 %	25.68 %
9	70.50%	21.31%	65.60 %	25.78 %
10	70.06%	21.52%	65.31 %	25.79 %
11	69.59%	21.69%	65.01 %	25.84 %
12	69.17%	21.85%	64.78 %	25.92 %

Table 5.9 Results of Forecast Error Variance Decomposition (FEVD):The Multiple Sources of Herding Effects of Compliment Behaviors

	% of Variance of Compliments toward CX Explained by itself, Positive Emotion and Rating Score in CRs			% of Variance of Compliments toward People/Service Explained by itself, Positive Emotion and Rating Score in CRs		
Period (Weeks)	(1) Compliments toward the CX	(2) Positive Emotion	(3) Rating Score	(1) Compliments toward the People/Service	(2) Positive Emotion	(3) Rating Score
1	52.07 %	34.54%	13.38%	76.31 %	13.37 %	8.67%
2	51.21 %	33.97 %	13.38 %	75.45 %	13.20 %	8.72 %
3	50.56 %	33.57 %	13.41 %	74.44 %	13.08 %	8.64 %
4	50.01 %	33.22 %	13.36 %	72.78 %	12.83 %	8.45 %
5	49.20 %	32.76 %	13.46 %	71.60 %	12.81 %	8.50 %
6	47.87 %	32.15 %	14.07 %	70.85 %	12.70 %	8.55 %
7	46.93 %	31.71 %	14.02 %	69.96 %	12.57 %	8.78 %
8	46.17 %	31.45 %	14.01 %	69.26 %	12.49 %	9.05 %
9	45.91 %	31.29 %	14.14 %	69.05 %	12.46 %	9.16 %
10	45.70 %	31.15 %	14.27 %	68.86 %	12.43 %	9.16 %
11	45.46 %	31.00 %	14.37 %	68.62%	12.39 %	9.21 %
12	45.25 %	30.89 %	14.45 %	68.43%	12.36 %	9.29 %

In a nutshell, we employ a VAR model that allows us to consider the spillover effects of previous MR components on later CR focal components. The results of **Tables 5.4** and **5.5** indicate the best combination of MR components to effectively improve customers' rating scores and expression of positive emotion and compliments in their CRs, as well as to mitigate their expression of negative emotion and complaints. We then use impulse response functions (IRFs) to focus on the cumulative effects (i.e., short-term effects over 4 weeks, and long-term effects over 12 weeks) of the different MR components on the focal CR components. The results reported in **Table 5.6** show the predictive impacts of different MR components for differing numbers of weeks ahead (i.e., 4, 8, and 12) and further validate our findings in **Tables 5.4** and **5.5**. Finally, to quantify the herding effects among customers, we conduct a variance decomposition analysis (FEVD) to explain the variance of focal CR components (customer rating behaviors and customer emotions), and this is reported in **Tables 5.7-5.9**. The results prove the existence of herding behaviors among customers on the TripAdvisor website.

5.5 Discussion and Conclusions

5.5.1 Discussion

RQ1-2: What are the "spillover" effects of MRs on the distinct elements of future CRs? What are the "herding effects" among customers' CRs?

In this paper, we define spillover effects as the impacts exerted by MR components on future customers' CR components. In comparison to previous contributions in the MR/CR arena, our research is the first empirical work to assess how a fairly comprehensive set of MR components can influence the focal CR components of future customers. We employ average weekly datapoints to examine the Online CR-MR

Echoverse at the firm's level. We summarize the results in **Table 5.4** and conclude that the spillover impacts are noticeable from certain MR components. For example, expressions that recommend guests and expression of interactions with guests cause positively accumulated responses in the CR components of rating scores, positive emotions, compliments, and referrals for future wider customers.

Some interesting spillover effects exerted by MRs that put forward explanations for previous unsatisfactory experiences must be noted. We found that offering an explanation in the t-5 period (MR posted five weeks ago) will cause desirable spillover effects on the positive emotions and compliments of current customers; however, the same MR component in the t-4 period (MR posted four weeks before) will cause undesirable spillover effects that increase the current customers' negative emotions and complaints. We thus suggest that it takes around one month (4 weeks) for firms to observe their guests' dissatisfaction and another week for them to take managerial action to remedy the failure that occasioned it. Another explanation is that current customers' postings at time t are influenced by the previous postings at time t-4(weeks) or t-5(weeks), which correlates to booking decisions that are made around one month (4 weeks) prior to a customer's traveling date. That is, the focal customers review others' postings at the time of making their hotel booking decisions. They will therefore check out the CRs for the hotel, and may come across not only the online CR but also the hotel's explanation in response to it. If, when they visit the hotel 4 weeks later, they discover that the same mistake is still being made or that the hotel's actions have not been in line with the explanation proffered 4 weeks ago, they are highly likely to post a negative CR. However, one week on, which is when hotels appear to be most likely to take corrective action after being alerted to an issue, the situation changes. The focal guest will have been exposed to the online details of other guests' unsatisfactory experiences but finds that during his or her visit, the issues have been resolved. This finding will exert positive carryover effects that are demonstrated in the guest's expression of positive emotions and compliments in his or her CR.

However, even positive spillover effects can backfire, and this has been recognized in this study. For example, offering explanations on the fourth lag (four weeks ago) will exert negative spillover effects on the rating scores, positive emotions, and compliment components of future customers' CRs. From the IRF results (**Table 5.6**), we conclude that offering explanations in MRs will cause a decrease in rating score, positive emotions, referrals, and revisit intentions in both the short (4 weeks) and long run (12 weeks); moreover, it will also cause an increase in negative emotions in both the short- and long-term.

We argue that that there is a time-frame effect as to how different MR components influence future CRs. Our results demonstrate that when later customers post their CRs, there is a relatively short time span during which they will be influenced by the contents of MRs that respond to previous customers' good experience. Unfortunately, the period during which future customers will be influenced by the contents of MRs responding to previous customers' bad experience is rather longer. Specifically, managers who offer explanations for earlier customers' bad experiences will generate double-edged effects on later customers' rating scores and emotion regulation. Generally, the most effective MR components for increasing future customers' rating scores in the short run (within 4 weeks) is the expression of sincerity and good interactions. The latter is also useful as a long-term strategy (12 weeks). To spark positive emotions in future customers and mitigate their negative emotions, the effective short-run (4 weeks) and long-run (12 weeks) strategies are the same: expressing good interactions and recommending guests in MRs.

Regarding herding behaviors among wider customers on the TripAdvisor website, this study is the first to simultaneously investigate in a single piece of research the spillover effects of MR components on later CR components, as well as the herding effects among CR components. Our findings differ from previous contributions on herding behaviors in online ratings, which focused on parsing out herding effects from multiple sources under different contingencies, or across multiple reference groups such as a network of friends versus a crowd network (Lee, Hosanagar, & Tan, 2015; Sunder, Kim, & Yorkston, 2019; Zhang & Godes, 2018). Our work employs a different perspective to disentangle different "sources" of herding effects among customers in that we decompose the variance of focal CR components as they are explained by themselves and by the other CR components. The FEVD results in **Table 5.7** show that herding behaviors exist among general customers on TripAdvisor. We found multiple sources of herding effects on customers' rating scores, positive emotions, negative emotions, referrals, and revisit intentions. The percentage of self-explanation ranges from 64.78% to 89.65% in the long run (12-week period). We conclude that earlier rating scores are the most critical source of customers' herding behaviors. Indeed, previous rating scores will not only exert herding effects on later customers' rating scores, but also on later customers' emotions. While considering the herding behaviors among CRs simultaneously, we find that MRs still have explanatory power of between 7%-8% to explain variances in customers' emotions and rating scores.

RQ3: How can we model the empirical results to label MR strategies that can highlight the positive or mitigate the negative emotions and rating behaviors of customers?

By summarizing the results of the VAR analysis in **Table 5.4.1**, the IRF analysis in **Table 5.6**, and the FEVD analysis in **Tables 5.7-5.9**, we offer the following conclusions.

(1) Regulating Customers' Emotions and Desirable Rating Behaviors

There are four MR components that are effective at regulating both future customers' emotions and their desired rating behaviors. These components are (a) expressions of sincerity, (b) expressions of interaction with guests, (c) guest recommendations, and (d) offering apologies for unsatisfactory experiences, all of which will increase the rating score, increase positive emotions, decrease negative emotions, and increase referrals and revisit intentions in the long run.

Future customers' rating scores and emotions will be influenced by shorter temporal effects by MRs to earlier customers' positive experiences but will be influenced by longer temporal effects by MRs to earlier customers' negative experiences. That is, from the firm's perspective, their response toward earlier customers' bad experiences will have longer-lasting influences on future customers' rating behavior, compared to those that respond to earlier customers' good experiences.

(2) Backfire Effects from Offering Explanations and Remedies in MRs

Several MR components need to be noted since they will backfire on the desired changes in the customer's rating score, emotions, and rating behaviors: offering explanations and remedying actions in MRs. Results in **Tables 5.4** and **5.4** and **Figures 5.7** and **5.8** show that offering explanations and remedies in MRs sometimes backfires. Specifically, offering an explanation will decrease future customers' rating scores, positive emotions, referrals, and revisit intentions as well as increasing future customers' negative emotions in the long run (within 12 weeks). These findings are counter-intuitive to both conventional wisdom and the service recovery literature, which posits the importance of active engagement with negative eWOM (Wang & Chaudhry, 2018) to restoring the relationship equity to the complaining customer and preventing negative eWOM from spreading to other customers (e.g., Hill et al., 2015). However, there are two perspectives regarding the suitability of the different approaches (affective versus cognitive) for reducing negative WOM. Homburg et al. (2007) posit that an affective approach through the expression of empathy is more effective in affect-intensive environments characterized by social interactions and spontaneous decisions. On the other hand, Gross (2002) indicates that some stimuli may be too emotionally intense for an empathic response to suffice, and the recipient may instead seek out explanations so that he or she can reappraise the situation. Hence, the more contagious the emotions in a negative WOM message, the more attention customers will pay to the message, generating stronger expectations about what ought to be done to remedy the situation (Hess, Ganesan, & Klein, 2003). Herhausen et al. (2019) reconcile these two perspectives and empirically confirm that when actively engaging in elaboration with the complaining customer, the increased use of empathy is more effective overall. However, if a negative eWOM message contains exceptionally intense high-arousal emotions, increasing the amount of explanation is more effective for preventing and mitigating the virality of negative eWOM. Our findings run contrary to these previous contributions. We find that offering explanations and remedies in MRs backfires, not only worsening the negative emotions and complaints of later customers, but also decreasing their positive emotions, rating scores, and complimentary behaviors. This finding does not mean that managers should ignore a negative post by a customer or that they should never provide explanations/remedies in their MRs. We argue, rather, that an empathic response is better than an explanatory response at containing negative eWOM on the TripAdvisor website and that firms should refrain from offering remedies unless they can deliver these within a meaningful timeframe.

In conclusion, to manage future customers' rating behaviors and emotions, we suggest that managers can leverage the benefits of providing MRs by showing sincerity, sharing interactive encounters with guests, publicly recommending their guests, and offering apologies that stop short at putting forward "excuses" for any unsatisfactory service encountered by guests. Finally, to leverage the herding effects among future customers, we suggest that managers focus more on the MR components that will cause positively accumulated effects on the rating score, this being the CR component that has the highest self-explanation of its own variance: 100% in the first period (after one week) down to 90% in the 12^{th} period (after 12 weeks). Moreover, customers' rating scores also help to explain other focal CR components, such as positive emotions, negative emotions, compliments, and referrals (the rating score is the second most important variable for explaining each of these variables' variance). Thus, we suggest managers should leverage three MR components that will cause the highest positive-accumulated responses to rating scores: expressions of (a) good interaction, (b) sincerity, and (c) recommendations of their guests. We suggest these MR components will boost customers' ratings scores and thereby increase future customers' rating scores through the herding effects among CRs.

5.5.2 Contributions

The extant CR and MR literature has addressed the benefits of CR as an avenue for consumers to express their opinions and evaluations of their customer experience (e.g., Baker, Donthu, & Kumar, 2016), and MR as an effective way for firms to manage and improve their online reputation (e.g., Proserpio & Zervas, 2017). Although extant studies have investigated the effectiveness of MR on later CR or the herding behaviors among CRs, the joint impacts of spillover effects of MR components on future CR components and the herding effects among focal CR components are unknown. Although some studies have examined the effectiveness of merely providing MRs, they do not differentiate between the managerial goals for managing customer emotion/customers' rating behaviors, in which different combinations of MR components will have varying impacts on distinct managerial objectives. Leveraging the concept of the echoverse from Hewett et al. (2016), we propose the "Online CR-MR Echoverse" framework to describe a communication system between customers and firms in the context of online review platforms. Drawing on several theoretical perspectives, including emotion regulation (Gross & Tompson, 2007), cognitive appraisal (Gross, 2002), affective infusion

(Homburg et al., 2007), in-group identification (Brown & Reingen, 1987), and service recovery (Hill, Roggeveen, & Grewal, 2015), we develop different components of MR and CR. The focal components of CR in our research are customers' positive and negative emotions, compliments, complaints, referrals, and revisit intentions. In line with the goal of "managing" the abovementioned focal CR components, the MR components can be categorized in several typologies: MR components related to content style, MR components related to in-group identification, MR components regarding emotional regulation, MR components regarding managing CR compliments, and MR components regarding managing CR complaints. Moreover, within the complex online CR-MR reverberation, we especially focus on the impacts of MR on future customers' focal CR performance. The major research questions answered in our study deal with the identification of spillover effects exerted by MRs on future customers' CR components, as well as the herding effects among raters. Integrating the strategic perspectives of emotion regulation, rating behavior management, and service recovery approach, we offer managers the ultimate combination of MR components to better manage repeat versus wider customers' emotion and rating behaviors as expressed in their future CRs.

Our research contributes to the literature in several ways. First, we build the conceptual framework of the Online CR-MR Echoverse, in which all CR and MR components echo all others and their own. In this framework, consumers' emotions and rating performance are theorized to link to the manager's communication vehicles in the echoverse. Our CR-MR Echoverse framework expands on the echo chamber idea widely postulated in the popular business press, extends the notion of the megaphone (McQuarrie, Miller, & Phillips, 2013), and enriches the reverberating echoverse for brand communication on social media sites (Hewett et al., 2016). Although there is a growing body of literature on the role of CR (or consumer WOM) and MR (or firm's online communications), our study is the first to assess how two reasonably comprehensive sets of MR/CR components can influence each other in the proposed online communication settings. Second, most of the extant literature captured CR and MR through volume or/and valence (e.g., Hewett et al., 2016; Homburg et al., 2015). We recognize that it is necessary to systematically explore CR and MR content with finer granularity. We thus process longitudinal, unstructured textual data from both customers' reviews and firms' responses online; we use a computational linguistic technique to develop a custom dictionary for our study, leverage a dictionary-analysis approach to transfer a unstructured, textual dataset into structured, numeric data, and analyze the data using econometric methods from a systematic perspective.

Third, we carefully unpack firms' MR impacts on customers' CRs through use of one unique dataset from the TripAdvisor website created from the unstructured textual data posted by customers and the managerial responses to these posts. We nuance the impacts of MRs by disentangling them as "spillover effects" on wider audiences in the contexts of online review platforms. We summarize the key takeaways to parsimoniously capture the insights gleaned from this research. To regulate wider customers' emotions and desirable behaviors, the leveraging of the components of sincerity, interaction, guest recommendations, and apology are suggested as effective in the MR. However, it must be noted that offering explanations in an MR will backfire in the long run in terms of the desired CR components. Herding behavior is noticeable among wider customers. To leverage the herding effects among wider customers, it is suggested that managers can focus on the MR components that will cause positively accumulated effects on rating scores, namely interaction, sincerity, and recommendation. To visualize the effects of selected MR components, **Figures 5.7** and **5.8** plot the over-time accumulated effects of a one-unit increase in one selected component on the increasing or decreasing patterns of a focal CR component: future customers' rating scores.

Fourth, to place our study in context within the extant literature, we briefly highlight a connection between our results and other mechanisms identified in the literature that can enrich the theoretical meanings of our findings. Based on the service failure and recovery literature (e.g., McCollough et al., 2000; Smith et al., 1999; Tax et al., 1998), some service researchers may hypothesize that the appropriate MRs can encourage focal consumers who left negative reviews to return and give unsatisfactory hotels a second try, possibly resulting in them leaving a refreshing, positive review. We find there are limitations to examining this potential hypothesis in our TripAdvisor dataset since the number of reviews left by returning consumers is too small to adequately verify this argument. Another perspective might be proposed (Bolton et al., 2013; Dellarocas & Wood, 2008; Resnick & Zeckhauser, 2002) by retaliation theory researchers. According to retaliation theory, negative ratings are underreported in bilateral review platforms because of the fear of retaliation (Fradkinet al., 2014; Hui et al., 2016; Zervas et al., 2015), the argument being that hotels can retaliate against negative reviews by disputing a reviewer's claim in an MR, which in turn may discourage future guests who have a negative experience from leaving a review altogether. Thus, hotels' retaliation behaviors may shift reviewer selection toward reviewers with higher ratings and on average, improve the ratings of hotels that respond in this way. We found that there is limitation to leveraging the retaliation argument as an explanation of our findings because there are no longitudinally increasing patterns in our dataset for customers' average rating scores toward the same hotel on TripAdvisor. Finally, we list guidelines that managers can use to regulate customers' positive/negative emotions and their rating behaviors in **Table 5.10.**

Table 5.10 Managerial Insights into Customer Emotions and Rating Behavior Regulation

Managerial Goals	Positive Emotion Regulation	Negative Emotion Regulation
Do:	· Recommend Guests · Expression of Good Interaction	· Using "He/She" · Admitting Mistakes · Expression of Manager's Name
Don't:	· Providing Remedies Backfires · Compliments of Guests Backfires	· Offering Explanations Backfires · Providing Remedies Backfires
Note:	· Offering Explanations Exerts Double-Edged Effects	

Managerial Goals	Referral Behavior Management	Revisit Intention Management	Rating Score Management
Do:	· Compliments of Guests · Expression of Empathy	· Recommend Guests · Expression of Good Interaction with Guests	· Recommend Guests · Expression of Manager's Name · Expression of Good Interaction with Guests
Don't:	· Recommend Guests Backfires	· Offering Explanations Backfires	· Offering Explanation Backfires · Providing Remedies Backfires

5.5.3 Limitation and Future Research Directions

Our analysis has several limitations that are worth exploring in future research. First, this study quantitively investigated one industry as it appears online. Further research could assess whether our results hold in other industries. Second, our data is limited to the specific online textual data (customers' reviews and managers' responses to these reviews) to represent the online echoverse components. There are other online channels used by customers and firms to express their opinions, which are not captured here. Third, since online CR/MR textual data might suffer from selection biases, a fully randomized experiment might be useful to validate the findings. Fourth and most importantly, it would be valuable for future research to extend this research and connect the online CR/MR data with the performance/transactional data of focal firms, such as sales, sales growth, booking rates, and stock prices, on a longitudinal scale to assess if the carryover or spillover effects of MRs could have real impacts on the actual business performance of the focal firms.

Chapter 6 Summary of Conclusions

This thesis aims to bridge the dynamic gap between the theoretical conceptualization and empirical analysis in the CX realm. Through three connected studies, we sought to understand: (1) the dynamic nature of the CX concept through the proposed research framework of the Customer Experience Trajectory (CET), comprised of different levels of CX performance states that are dynamically influenced by migration mechanisms; (2) the evolution of CX performance states from both the individual and collective levels; (3) the dynamic influences of different dimensions of perceived CX, as well as management actions in the real-world contexts, on the evolution of CX performance states at the individual level; (4) the dynamic influences of the proposed ARCI value co-creation mechanisms on the evolution of CX performance states at the firm level; and (5) the dynamic interactions between the experience providers and receivers in the proposed Online CR-MR Echoverse, where we depict an online communication environment for both firms and customers.

6.1 Summary of the Empirical Findings

In this section, we will briefly recap the findings of the three empirical studies, crystallizing our understanding of the findings. Figure 6.1 indicates the flows of reasoning from section 6.1.1 to section 6.1.3, so we will first summarize the answers to the research questions addressed in study 1 regarding the dynamics of the CX trajectory from the customers' perspectives. The second step indicates the answers to the research questions of study 2 regarding the dynamics of the CX performance trajectory from the firms' perspectives. The third step involves briefly answering the research questions of study 3 in terms of the reverberation dynamics between the experience receivers and providers.

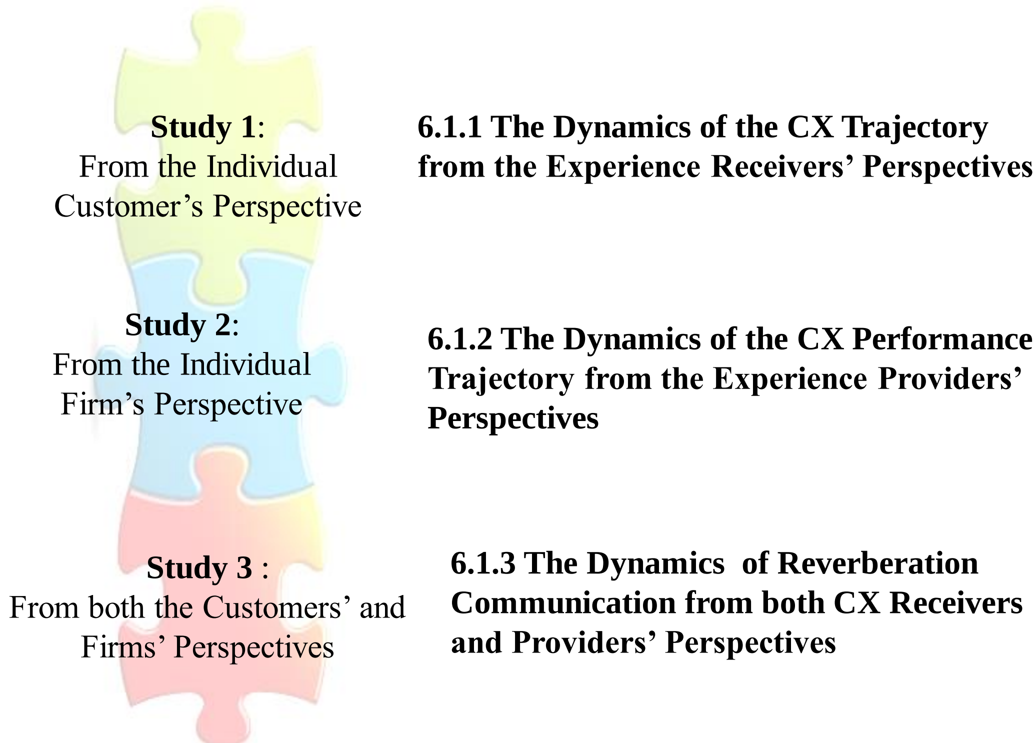


Figure 6. 1 The Flows of Reasoning among the Three Studies

6.1.1 The Dynamics of the CX Trajectory from the Experience Receivers' Perspectives

Study 1 raises a substantive question: are the CXs of existing, repeat customers always "static"? That is, will the CX trajectories of repeat customers remain constant? If not, will repeat customers have fixed perceptions and behave statically throughout their CX trajectories? For marketing practitioners, the consequence of ignoring or misunderstanding this phenomenon means that a piece is missing from the overall picture of CX management regarding the retention of existing repeat customers. We will now summarize the empirical results that aimed to answer the following three research questions that were addressed in study 1.

RQ1: How do repeat customers' CX performance states evolve over time, and can they be segmented into different groups with different evolutions of CX performance states?

Throughout the repeat customers' CX trajectories, we identify three hidden CX performance states at the individual level. These are (1) the Neutral (N) state with the lowest summative score for the desired behavioral variables (revisit, referral, and compliment) and the highest complaint score; (2) the Positive-Active (P-A) state with a medium score for compliments but higher scores for referral and revisit performance; and (3) the Positive-Passive (P-P) state with the highest score for compliments but lower scores for referral and revisit performance than the P-A state. Moreover, repeat customers can be segmented into two groups that exhibit distinct behaviors: (1) more complimentary with lower engagement i.e., the group has a lower level of customer engagement (e.g., expression of revisit, referral, and complaint) but is more complimentary (i.e., has a higher compliment score); and (2) less complimentary with higher engagement, i.e., the group has a higher score for revisit, referral, and complaint expression but a lower compliment score. The initial state probabilities of being in a CX performance state (N, P-A, or P-P) for Group 1 are 6%, 19%, and 75%; these probabilities are 10%, 43%, and 47% for Group 2. Hence, a repeat customer tends to begin in a positive-passive (P-P) state for both groups.

Furthermore, the most likely destination for Group 1 (the more complimentary, lower engagement group) is the P-P state. For Group 2, the most likely destination is the P-A state. When the repeat customers in Group 1 move to an N or P-A state, they are more likely to return to the P-P state. Group 2 tends to end up in a P-A state. This group is also more likely to move down from their first trajectory state to a lower N state than are the members of Group 1. However, we suggest that the consumers in Group 2, with their higher level of engagement, present valuable signals for managers since this segment devotes more efforts to attracting new clients through referrals and recommendations, and expresses strong revisit intentions to the experience provider.

RQ2: Which migration mechanisms influence the transition across the CX performance states between different segments? How can we decompose the short- and long-term effects of the migration mechanisms between the different segments?

To answer this research question, we summarize the empirical results into four categories: (1) the short-term effects of the four dimensions of CX (mechanism 1) on the state-dependent distributions; (2) the short-term effects of the related managerial variables (mechanism 2) on the state-dependent distributions; (3) the long-term effects of the four CX dimensions (mechanism 1) on the changing transitional probabilities; and (4) the long-term effects of the managerial variables (mechanism 2) on the changing transitional probabilities.

Pertaining to the short-term effects of the four dimensions of CX (mechanism 1) on the state-dependent distributions, which determine repeat customers' CX performance in the current period, the empirical results show that affective CX has a positive relationship with the P-P state but a negative relationship with the P-A state. Interestingly, both cognitive and social CXs have a negative relationship with the P-P state but a positive relationship with the P-A state. We thus suggest that repeat customers in the P-A state have a higher expression of revisit and referral intention than those in the P-P state, which requires stronger responses to the cognitive elements (through the thinking process) and social elements (through the social process) of their staying experiences. Moreover, affective CX has a positive relationship with the P-P state but a negative one with the P-A state. We suggest that repeat customers in the P-P state express a stronger level of compliments than those in the P-A state; hence, the P-P state requires stronger responses by the affective components (e.g., positive emotions). Finally, we find that the less affective and physical the CXs, the greater the likelihood of being in the N state, where consumers will complain about their dissatisfactory experiences through a social process; this is reflected in the positive relationship with the social components of their staying experiences.

Regarding the short term effects of mechanism 2 on the state-dependent functions (i.e., the management-related variables that comprise the six Airbnb experience evaluation criteria that the experience providers can control), we find significantly positive relationships between communication, cleanliness, and location, and the P-P state, but significantly negative relationships between check-in and value, and the P-P state. The negative coefficients in the P-P state suggest that, the more prolonged the check-in process, the lower the likelihood of being in the P-P state and, the higher the price, the lower the probability of being in the P-P state in terms of compliment expression. In contrast, we find significantly negative relationships between communication, cleanliness, and location, and the N state but a positive relationship between check-in and the N state. The results for the N state suggest that, the lower the quality of the communication, cleanliness, and convenience of the location, the greater the probability of being in the N state, which is represented by the highest complaint score and the lowest desired behavioral score. Moreover, the longer the check-in process, the higher the probability of being in the N state.

In terms of the long-term effects of the different dimensions of CX (mechanism 1) on the probabilities of transitional change, the affective CX not only increases the probability of shifting up but also reduces the likelihood of moving down. Specifically, for Group 1 in the P-A state and the N state, the more affective the CX, the higher the probabilities of transferring to the P-P state. Moreover, for the same group in the P-P state, the more affective the CX, the lower the likelihood of declining to the N state. However, social CX seems to backfire for Group 1, as it exerts the opposite effect on the desired transitional direction. Empirical results show that, the higher the level of social CXs, the higher the likelihood of moving from the P-P state to the N state.

On the other hand, for Group 2, with higher engagement but fewer compliments, affective CX not only increases the probability of shifting up but also reduces the likelihood of moving down. For Group 2 members in the P-A state and the N state, the higher the number of affective CXs, the higher the probability of transferring to the P-P state. Moreover, the higher the level of affective elements in the customers' experiences, the lower their likelihood of descending from the P-A or the P-P state to the N state, respectively. Similarly, the higher the cognitive CXs, the greater the probability of transferring from the N state to the P-P state. For the same group in the P-P and P-A states, the higher the level of the cognitive dimension within their experiences, the lower the likelihood that consumers will descend from either of the higher states to the N state. In addition, for Group 2 in the P-P and P-A states, the higher the level of physical-sensory components in their experiences, the less likely they are to descend to the N state.

Interestingly, social CX also backfires for this group. The empirical results show that, for Group 2 in the N state, the higher the number of social CXs, the lower the probability that they will transition to the P-P state. Similarly, the higher the number of social CXs, the greater the likelihood of declining from the P-P state to the N state.

Turning to the long-term effects of the six experience evaluation criteria on the Airbnb website (mechanism 2) that the experience providers can control, we find that, for Group 1, the perceived convenience of location and the quality of the providers' communication will increase their probability of moving up from the P-A state to the P-P state, and also decrease their probability of moving down from the P-P state to the P-A state. Moreover, for the same group, a perceived lengthy waiting time and check-in process will see an increase in their probability of going down from the P-P state to the N state. On the other hand, a perception of high cleanliness reduces the likelihood of moving down from the higher states to the N state for the repeat customers in Group 2.

Generally, for the repeat customers in Group 1, whose most likely potential destination is the P-P state, increasing this group's perception of affective CX will not only boost their likelihood of moving up from the N state to the P-P state but will also decrease their likelihood of moving down from the P-P state to the N state. On the other hand, mechanism 2 (the six evaluation criteria on the Airbnb website) is not an effective migration tool for managers wishing either to boost upward migration or forestall downward switching. Finally, two backfire effects need to be highlighted in Group 1. That is, the social dimension of CX in mechanism 1 and the check-in process in mechanism 2 will exert backfire effects on the path from the P-P state to the N state, thereby increasing the likelihood of downward migration. For the repeat customers in Group 2, for whom the P-A state is their most likely destination, both mechanisms 1 and 2 are more effective when used as prevention strategies to decrease the downward probabilities than as promotion strategies to increase this group's upward likelihood. Interestingly, social CX also exerts backfire effects on this group. That is, increasing Group 2's perceptions of the social dimension of CX will not only inhibit their upward migration from the N state to the P-P state, but also aggravate their downward probabilities from the P-P state to the N state.

RQ3: How will different segments of repeat customers respond to migration mechanisms as they transition across their CX performance states? More specifically, how can practitioners benefit from the examination of segmented repeat customers who respond differently to migration mechanisms as they transition across the CX performance states?

To summarize the answers arising from the empirical results for RQ3, we provide **Table 6.1**, which contains the rules of thumb that managers can use to deploy the relevant migration strategies toward different groups, given their desired transitioning objectives. In a nutshell, for the repeat customers in Group 1, who express more compliments but have a lower level of engagement and whose most likely destination is the P-P state, increasing their perceptions of affective CX is useful as both a promotion strategy to boost upward migration and a prevention strategy to decrease downward migration. For the repeat customers in Group 2, who express fewer compliments but have a higher level of engagement and whose most likely destination is the P-A state, both mechanisms can be used more effectively as prevention strategies to decrease the likelihood of a downward turn than as promotion strategies to increase the likelihood of going up.

Interestingly, the social dimension of CX exerts backfire effects on both groups. It not only increases the downward probabilities for Group 1 and Group 2, but also decreases the upward probabilities for Group 2.

Drawing on both Herzberg's motivation-hygiene theory (1987) and Kranzbühler, Kleijnen and Verlegh's perspective regarding satisfiers and dissatisfiers throughout the CX trajectories (2019), we contend that the prevention mechanism can be seen as Herzberg's hygiene factors and Kranzbühleret et al's dissatisfiers that adhere to a certain threshold to avoid consumers having a negative experience but have limited upside potential (Vargo 2007). Thus, in this study, the prevention mechanism that decreases the downward probabilities of moving from higher CX states to lower CX ones is in line with the concept of dissatisfier/hygiene factor, deceasing consumers' satisfaction when it is not executed well. On the other hand, the promotion mechanism that increases the upward likelihoods of moving from lower states to higher ones corresponds to Herzberg's motivation factor and Kranzbühler et al's satisfier, related to the value enhancing features throughout the CX journey (Vergo 2007) and contributing to consumers' satisfaction when executed well.

Table 6.1 The Managerial Takeaways for CX Practitioners

Group 1 with a Profile of More Complimentary with Lower Engagement	
The Desired Transitions	**The Suggested Effective Migration Mechanism**
1. Retaining Group 1 in the P-P State	· The P-P State is the generic "destination" for Group 1 **Leveraging the results of the short-term effects on state-dependent distributions:** · Mechanism 1: Increasing repeat customers' affective dimension CX in the current period · Mechanism 2: Increasing the perceived quality of the communication, cleanliness, and convenience of the location in the current period
2. Retaining Group 1 in the P-A State	**Leveraging the results of the short-term effects on state dependent distributions:** · Mechanism 1: Increasing repeat customers' cognitive CX, social CX and physical CX in the current period · Mechanism 2: Increasing the perceived quality of cleanliness in the current period.
3. Promoting Group 1 from the N State to the P-A/P-P State	**Leveraging the results of the long-term effects on changing transition probabilities:** · Mechanism 1: Improving the perceived affective dimension of CX · Mechanism 2: None
4. Preventing Group 1's demotion from the P-P/P-A	**Leveraging the results of the long-term effects on changing transition probabilities:** · Mechanism 1: Improving the perceived affective CX

State to the N State	· Mechanism 2: None · **Backfire Effects: Increasing the perceived social dimension of CX will increase the probability of drifting downward from the P-P state to the N state**
Group 2 with a Profile of Less Complimentary with Higher Engagement	
The Desired Transitions	**The Suggested Effective Migration Mechanism**
1. Retaining Group 2 in the P-A State	· **The generic "destination" for Group 2 is the P-A state.** **Leveraging the results of the short-term effects on state dependent distributions:** · Mechanism 1: Increasing repeat customers' cognitive CX, social CX and physical CX in the current period · Mechanism 2: Increasing the perceived quality of cleanliness in the current period.
2. Retaining Group 2 in the P-P State	**Leveraging the results of the short-term effects on state-dependent distributions:** · Mechanism 1: Increasing repeat customers' affective dimension CX in the current period · Mechanism 2: Increasing the perceived quality of communication, cleanliness and convenience of location in the current period
3. **Promoting** Group 2 from the N State to the P-A State	**Leveraging the results of the long-term effects on changing transition probabilities:** · Mechanism 1: Improving the cognitive dimension of CX

	• Mechanism 2: None
4. **Promoting** Group 2 from the N State to the P-P State	**Leveraging the results of the long-term effects on changing transition probabilities:** • Mechanism 1: Improving the affective dimension of CX • Mechanism 2: None • ***Backfire Effects: Increasing the perceived social dimension of CX will decrease the probability of moving upward from the N state to the P-P state.***
5. **Preventing** Group 2 from falling from the P-A State to the N State	**Leveraging the results of the long-term effects on changing transition probabilities:** • Mechanism 1: Improving the affective, cognitive, physical, social dimensions of CX • Mechanism 2: Improving the cleanliness perception will help to prevent drifting downward
6. **Preventing** Group 2 from falling from the P-P State to the N State	**Leveraging the results of the long-term effects on changing transition probabilities:** • Mechanism 1: Improving the affective cognitive and physical dimensions of CX • Mechanism 2: Increasing repeat customers' perceptions of the cleanliness and convenience of location will prevent Group 2 from moving downward • ***Backfire Effects: Increasing the perceived social dimension of CX will increase the probability of drifting downward from the P-P state to the N state***

6.1.2 The Dynamics of the CX Performance Trajectory from the Experience Providers' Perspectives

Study 2 aims to complement the picture of the CET framework depicted in Study 1. Study 1 focuses on the dynamics of existing, repeat customers' evolution among the different states. The proposed CET framework depicts individuals' migration across the Neutral (N) CX performance state, the Positive-Active (P-A) state, and the Positive-Passive (P-P) state. These states are defined as the individual's CX performance from the lower to the higher levels. In study 2, the research focus changes to the firms' CX performance and the dynamic influence exerted by the proposed migration mechanisms on the trajectories of that performance. In study 2, the CX performance states are defined at the firm's level according to the collective perceptions of their existing customers/clients. Furthermore, the migration mechanisms proposed in the two studies differ in two ways. The objective of the migration mechanisms in study 1 is to offer an understanding of the "dynamic phenomenon" of the individual customer's CX trajectory. Therefore, the migration mechanisms are proposed at the same (individual) level, examining the dynamic influences of the focal customers' perceived experience on their transitions among the different CX performance states. Complementarily, study 2 sheds light on the firm's CX performance states at the collective level. Hence, the migration mechanisms are proposed from a standpoint that can be managed, designed, or at least partially controlled by the firms.

In study 2, we leverage the value co-creation theory (Prahalad & Ramaswamy 2004), to argue that experience is co-created by firms and customers as a joint initiative, through which experience providers (firms) and experience receivers (consumers) together create an experience. In the experience co-creation process, both parties engage in “activities”, “interactions”, and “resource integrations” that occur in distinct experience “contexts.” Furthermore, drawing upon the service-dominant logic (Vargo & Lusch, 2004), we assert that value is generated and perceived within the co-creation process of experience. The activities and resources provided by the firm, and the interactions between and the contexts of the customers and the firm will determine the value of the firm’s CX performance, as perceived by their customers. In study 2, based on this theoretical underpinning, we propose a migration mechanism, namely the ARCI model, that comprises the firms and customers' activities and resources, service contexts, and interactions at the collective level. Study 2 argues that the positive/negative perceptions of the ARCI model will dynamically influence the firms' trajectories/evolutions among their CX performance states. We summarize the empirical results to answer three research questions in study 2.

RQ1: How many latent states of CX performance can be identified at the firm’s level?

We identify four states for the experience providers’ CX performance. These four states differ substantially in terms of the rating score received from their customers. We refer to the four CX performance states as lower, medium, high, and very high, denoted as L, M, H, and H^+, with corresponding CX performance scores of 5.63, 7.23, 8.36, and 9.21. The initial probabilities of being in the L, M, H, and H^+ performance states are 9%, 31%, 32%, and 27%, respectively.

RQ2: How does the trajectory of firms’ CX performance evolve over time?

The L state is characterized by lower levels of CX performance, expressed by the 5.80 average rating score. This lower performance state also exhibits "positive future movement." Firms in the L state move to a stronger state 54% of the time and remain in the same state 46% of the time. The M state exhibits a moderate level of CX performance, represented by the average rating score of 7.32. It is the stickiest state (74% remain here each period), and while 14% of firms move up, 11% of firms move down. The H state exhibits firms' CX performance with an average rating score of 8.32. Firms in the H state move to a higher performance state 23% of the time, a lower performance state 31% of the time, and remain in the H performance state 46% of the time. The H^+ state is the highest level of CX performance, represented by an average rating score of 9.23. In terms of migration, it is relatively sticky (71% remain in this state each period). However, this figure indicates that firms in the H^+ state have a 29% probability of dropping to a lower performance state. This reinforces the importance of having migration mechanisms to motivate firms to move from a lower CX performance state to a higher one, or to prevent their deterioration from a higher performance state to a weaker one.

RQ3: How do the positive and negative migration mechanisms composed of the ARCI components influence the transition across different states of CX performance? That is, given a firm's current CX performance state, what is the most effective strategy/element for migrating it to a higher performance state or preventing it from moving to a lower one?

We first summarize the dynamic effectiveness of the positive value co-creation mechanisms (the ARCI element variables extracted from guests' positive comments) across six upgrade migration paths. This allows us to highlight the most effective strategies for upward migration. The first positive value co-creation element, “firm’s activities”, significantly increases the probability of firms moving from a lower performance state (L) to a higher one (M, H, H^+). The second element of the positive ARCI mechanism is “customers’ activities"; this is less effective with regard to upward migration. Interestingly, the third and fourth elements of positive mechanisms, “firms’ resources” and “customers’ resources”, exert backfire effects on the upward migration paths. The positive perceptions of firms’ resources reduce the likelihood of firms transitioning from an M state to an H^+ state and from an H state to an H^+ state. Positively perceived customers’ resources also decrease the likelihood of a transition from the H state to the H^+ state. For the fifth element of the positive ARCI mechanism, positively perceived contexts have significant impacts on shifting a firm’s performance from the M state to the H state, as well as from the M state to the H^+ state and from the H state to the H^+ state. The positive element of “interaction” between firms and customers significantly increases the probability of an upward transition from the L state to the M state, the L state to the H state, the M state to the H state, and the H state to the H^+ state.

Concerning the negative mechanisms of the ARCI model, the first element of negative migrations is customers’ negative perceptions of “firms’ activities”, which has the significant impact of shifting a hotel's CX performance from the H^+ state to the H state and from the H state to the L state. The second element is negative perceptions of “customers’ activities", which increase the likelihood of moving downward from the H^+ state to the H state. The third and fourth elements, the negative perceptions of “firms’ resources” and “customers’ resources”, are detrimental to the higher performance states. The former affects firms’ downward migration from the H^+ state to the M state and from the H^+ state to the L state, while the latter increases the likelihood of a detrimental transition from the H^+ state to the H state. The fifth element of the negative mechanism, the perceived negative "contexts", exerts deteriorating effects that shift a firm's CX performance state from the H^+ state to the H state. Finally, the perceived negative "interactions" between firms and customers significantly worsen firms' performance from the higher to the lower states. **Table 6.2** provides the managerial takeaways of these dynamic migration strategies for firms.

Table 6.2 Three Major Managerial Takeaways that emerge from the Empirical Results of Study 2

Takeaway 1: The short-term effects (state-dependent effects) exerted by the four dimensions of CX perceptions
· The affective dimension of CX is the most critical factor in determining firms' current state of CX performance. · A lower level of affective CX will shape lower CX performance, presented as a lower rating score. · A higher level of affective CX will determine higher performance states in the current period, presented as higher rating scores.
Takeaway 2: The long-term effects (migration effects) exerted by the positive mechanism
· Increasing firm's activities to cultivate positive contexts and encourage positive interactions are effective strategies for boosting upward migrations. · Improving customers' positive perceptions of the firm's activities is the strategy most likely to propel the firm's CX performance out of the lowest performance (L) state.
Takeaway 3: The long-term effects (migration effects) exerted by the negative mechanism
· Increasing the negative perceptions of the firms' activities and resources, and the service contexts and interactions, will together deteriorate firms' CX performance from the higher states to the L state, partially offsetting the benefits generated by the positive mechanism mentioned in Takeaway 2. **The notifications for managers of hotels listed on booking.com:** · Customers' negative perceptions of the hotel staff, facilities, and comfort on booking.com will deteriorate the hotels' CX performances. · Managers must be aware that the evaluation criteria on Booking.com are more influential as a negative mechanism that injures performance than as a positive mechanism for improving firm's CX performance states.

6.1.3 The Dynamics of Reverberation Communication from both the CX Receivers and Providers' Perspectives

Finally, in study 3, we integrate the perspectives of both the experience providers and the experience receivers. This study elucidates the dynamic interactions between the reviews posted by customers regarding their received services or perceived experiences and the firms' managerial responses (MRs) to these customer reviews (CRs). To encapsulate an online communication environment in which firms and customers verbally (albeit electronically) contribute and are influenced by each other, we leverage the concept of the "echoverse" (Hewett et al., 2016), thereby striving to reflect the dynamic interactions between firms and customers in the rating platform context.

Through the proposed research framework, the online "CR-MR Echoverse", we investigate the dynamic reverberations among CRs and MRs. The CR-MR Echoverse integrates several theoretical lenses, including emotion regulation, cognitive appraisal, affective infusion, similarity perception, service recovery, and herding behaviors. The building blocks of the CR-MR Echoverse include distinct CR components and MR components, all of which comprise a reverberation system that portrays the spillover effects of MR components on future CR components and the herding effects evident in the CR components. We draw on two perspectives: customers' emotion regulation and rating behavior management, to tailor the best combinations of MR components as response tactics that firms can use when engaging in online conversations with their customers.

RQ1: What are the major elements of online MRs and online CRs, respectively, that firms should strive to influence?

In study 3, building on our literature review and the previous contributions, we suggest the following compositional elements for online MRs. In an extension of Herhausen et al. (2019)'s work, we consider four major categories comprising firms' online MRs: (1) the presence of MR; (2) its length; (3) the linguistic style including the tone, a linguistic style that matched that of the customer, variation in words across all firm responses; and (4) its contents, including expressions of thanks, offering apologies, expressing sympathy, offering explanations, providing remedies, offering compensation, and showing sincerity. Regarding the compositional elements of online CR, in terms of the theoretical aspect, we also consider the practicalities of a manager's primary objective in responding to a CR, which is to send out signals to potential future consumers. One way to reveal the critical components of the CR is to consider which elements of CRs are emphasized/valued most by the firms and the potential customers. We propose that there are seven major compositional elements of online CR: (1) positive emotions, (2) negative emotions, (3) rating score, (4) compliments, (5) complaints, (6) revisit intentions, and (7) referrals.

RQ2-1: What are the "spillover" effects of MRs on the distinct elements of the ensuing online CRs?

We define spillover effects as the impacts exerted by MR components on the CR components of subsequent customers. We employ average weekly data points to examine the online CR-MR Echoverse at the firm level. We conclude that the spillover impacts are noticeable from distinct MR components. For example, commending guests and expressing good interactions with guests in MRs cause the customers who follow these MRs to increase their rating scores, expressions of positive emotion, compliments, and referrals in their CRs.

Moreover, some interesting spillover effects can be identified. The results show that an MR posted 5 weeks ago will cause the desirable spillover effects to increase subsequent customers' positive emotion and compliments; however, the same MR component posted 4 weeks ago will backfire, triggering undesirable spillover effects that increase the subsequent customers' negative emotion and complaints. We offer two interpretations of this double-edged effect of offering an explanation in MRs for previous poor customer experiences. First, if we view the issue from the perspective of potential/future customers, these customers might research and book the focal hotel 5 weeks (just over a month) before the planned week of travel, when they will see earlier guests' dissatisfied comments and the firm's response to these. When they arrive at the hotel, they will be pleasantly reassured if they see that the hotel has followed through on its response, and this will be reflected in their own CR. Alternatively, they may research and book the focal hotel 4 weeks before the planned week of travel, noting from their research that a specific issue was mentioned a week ago by previous guests but that the hotel has responded to those comments. However, on their arrival, they discover that the situation remains unchanged. Their disappointment will likewise be reflected in their own CR's rating score and emotions.

The other perspective for viewing this is through the lens of the firms and their managers. It might take as long as 5 weeks for firms to observe their guests' dissatisfaction and decide how to act to resolve the issue that caused it, and perhaps a further week to recover from the service failure.

The backfire effects from offering explanations are further confirmed by the IRF tests. We conclude that offering an explanation in MRs will cause a decrease in the rating score, positive emotion, referral, and revisit intention in both the short- (4 weeks) and long-term (12 weeks). Moreover, it will cause an increase in negative emotion in both the short- and long-term.

Based on the IRF tests, the most effective MR components for increasing a hotel's future rating score in the short-term (one month) is an expression of sincerity and good interactions with guests. In the long-term (three months), the most effective MR component is to express good interactions with guests. To stimulate positive emotions in future customers and mitigate their negative emotions, the most effective one-month and three-month strategies are identical: expressing good interactions and recommending guests in MRs. To encourage future customers' referral behavior, expressing empathy in the MRs is effective in exerting short-term (1-month) and long-term (3-month) effects on future CRs. To increase future customers' revisit intention, the expression of good interactions with guests is effective as both a short- and long-term strategy to influence future CRs.

RQ2-2: What are the "herding effects" among CRs ?

In terms of the herding behaviors among wider audiences online, the FECD results show that there are noticeable herding behaviors within customers' rating behaviors. Specially, future customers' rating scores, referrals, and revisit intentions can be largely influenced by previous customers' rating scores, referrals, and revisit intentions. Moreover, we find the phenomenon in terms of multiple sources of herding effects. That is, regarding customers' positive and negative emotions, in addition to being influenced by previous customers' emotions, there is another CR component, previous rating score, that can explain more that 20% of the variance in current customers' emotions. Another multiple source of herding effects is customers' complimentary behaviors.

We find herding effects among customers' complimentary behaviors, which are not only influenced by previous customers' compliments but also affected by previous customers' positive emotions and rating scores. Our empirical results prove that customers adjust their emotions and rating behaviors in line with the online rating information of the crowd. That is, to conform with the crowd's opinion, customers' emotions and rating behaviors are positively related to previous customers' emotions and rating behaviors. We further conclude that previous rating score is the most critical source of customers' herding behaviors. Previous rating scores will exert herding effects not only on subsequent customers' rating scores, but also on later customers' emotions. Through considering the herding behaviors among all of the CRs simultaneously, we find that MRs still possess an explanatory power of 7%-8% to explain the variances in customers' emotions and rating scores.

RQ3: How might managers model the above results to label MR strategies that seek to promote positive CRs or suppress negative ones as dynamic online MR strategies? More specifically, how can practitioners model the empirical results to label MR strategies that will stimulate customers' positive emotions, mitigate negative their

emotions, and improve their rating scores, referrals and revisit intentions?

Two points should be highlighted from our empirical results to form useful MR strategies, discussed as follows.

Highlight 1: Offering explanations and remedies exerts backfire effects on future rating scores

Turning to how MRs may be leveraged to manage future customers' CRs, two MR components must be noted as potentially hazardous: offering an explanation and providing remedies. These will rebound on the firm, reversing the desired changes in the customer' rating scores, emotions, and rating behaviors. The empirical results show that both offering an explanation and providing remedies in MRs will decrease subsequent customers' rating scores, positive emotions, referrals, and revisit intentions. These tactics will also increase their negative emotions in the long-term. In summary, to manage the desirable rating behaviors of future customers, we suggest that managers should leverage the benefits of showing sincerity, having great interactions, recommending guests, and offering an apology in their MRs. However, they should not offer an "excuse" for the unsatisfactory service encountered by the guests.

Highlight 2: How can we leverage the herding effects that exist among wider audiences?

To leverage the herding effects among wider customers, we suggest that managers should place greater focus on the MR components that will exert positively accumulated effects on rating scores, which is the highest self-explanation CR component. Moreover, wider customers' rating scores also help to explain other focal CR components, such as positive emotion, negative emotion, compliments, and referrals, acting as the second most important variable for explaining the variances in these components. We suggest three MR components that will cause positively accumulated responses of rating scores: expression of interaction, sincerity, and recommendation of guests. To summarize the answers found in the empirical results for RQ3, we provide **Table 6.3**, which displays the managerial insights that practitioners can use to craft the best combinations of MR components for regulating subsequent customers' emotions and rating behaviors.

Interestingly, the results for study 3 reveal contracting effects between regulating positive CR versus negative CR through MR components simultaneously, represented by the backfire effects exerted by providing explanations/remedies in MRs on later customers' positive emotions and rating scores. Moreover, the MR strategy is relatively effective in regulating customers' positive emotions, in line with the findings of the meta-analysis of Kranzbühler et al. (2020). Their meta-analysis results indicate that customers' positive emotions show consistently stronger effects than do negative emotions on the consequential behaviors. Specifically, customers' gratitude exerts the highest effects on their later evaluation and sharing behavior (Kranzbühler et al. 2020), which echoes the proposed MR strategies in this current study: recommending guests and expressing good interactions with customers in MRs to boost positive emotions, rating scores and customers' compliment behaviors. On the other hand, customers' anger exerts a lower strength but more prevalent negative affects across the evaluation, purchase and sharing results (Kranzbühler et al. 2020), which reflects the findings about offering explanations and remedies in MRs to respond to negative CRs so that the backfire effects will prevail among later customers' emotions and rating behaviors.

Table 6.3 Managerial Insights into Customer Emotions and Rating Behavior Regulation

Indicating the Significant Components of Previous MRs on Current CR's Focal Components (Customers' Rating Score and Customer Emotions)				
Managerial Objectives	**Influential Time Frame: $MR_{(t-j)} \rightarrow CR_t$**			
	t-5(weeks)	**t-4(weeks)**	**t-3(weeks)**	**t-1(week)**
(1) Rating Score Management	• Offering explanations • Providing Remedies Backfire	• Offering explanations backfire	• Expressing good interactions	• Recommending guests
(2) Positive Emotion Management	• Providing Remedies Backfire	• Expressing he/she • Offering explanations backfire		
(3) Negative Emotion Management	• Providing Remedies Backfire	• Offering explanations backfire	• Expressing good interactions	• Recommending guests

Predicting the Effects of Current Components of MRs (Expressing Good Interaction, Sincerity, and Recommending Guests) on the Future Performance of CRs (Rating Scores and Customer Emotions)			
Managerial Objectives	**Influential Time Frame: $MR_t \rightarrow CR_{(t+j)}$**		
	t+4(weeks)	**t+8 (weeks)**	**t+12 (weeks)**
(1) Rating Score Management	• Expressing good interaction (+5%) • Recommending guests (+4%) • Expressing Sincerity (+5%)	• Expressing good interaction (+15%) • Recommending guests (+9%) • Expressing Sincerity (+7%)	• Expressing good interaction (+26%) • Recommending guests (+11%) • Expressing Sincerity (+11%)
(2) Positive Emotion Management	• Expressing good interaction (+13%) • Recommending guests (24%	• Expressing good interaction (+32%) • Recommending guests (57%)	• Expressing good interaction (+58%) • Recommending guests (+78%)
(3) Negative Emotion Management	• Expressing good interaction • (-1%) • Recommending guests (-5%)	• Expressing good interaction (-6%) • Recommending guests (-15%)	• Expressing good interaction (-12%) • Recommending guests (-21%)

6.2 Contributions to Theoretical Development

Through Study 1 and 2, we established the foundations for bridging the dynamic gap between the previous conceptual and empirical research on customer experience. These two papers complement each other and present a complete picture of the “Customer Experience Trajectory (CET)” from both the individual and firm perspectives. The proposed CET framework not only depicts and explains the evolution/dynamics of CX performance but also offers actionable strategies for managing the CET framework dynamically. Study 3 goes further and creates a reverberating echoverse for online communication between customers and firms. This adds supplemental value that, together with the results of paper 1 and paper 2, informs an emerging theory of customer experience management (CXM) from a dynamic perspective.

6.2.1 Bridging the Dynamic Gap between Conceptual and Empirical Studies on Customer Experience (CX)

Drawing on previous scholars’ contributions (e.g., De Keyser et al., 2015; Gahler et al., 2019; Homburg et al., 2015; Lemon & Verhoef, 2016; Verhoef, Kooge, & Walk, 2016), we define CX as a customer’s subjective response during dynamic encounters/interactions with experience providers, including but not limited to firms, firms’ partners, personnel, brands, products, services, or technology, that holistically evokes the customer’s multidimensional responses during the CX journey. Further, the CX definition should be understood, from the perspective of the focal customer's CX journey, as an iterative and dynamic process, built up through multiple touchpoints, that flows across multi-stages, incorporating past/previous CXs as well as external factors.

Such complexity of conceptualization, involving multiple experience providers, touchpoints, channels, and time-points, reflects the dynamic nature of CX and makes empirical work in this field challenging for CX scholars (Gahler et al., 2019). That is, although previous scholars suggest that the CX concept can be understood through the perspective of the customer journey or dynamic process (e.g., Bonchek & France, 2014; Edelman & Singer, 2015; Lemon & Verhoef, 2016), little is known about how we might empirically capture the evolution of customers' perceived experiences throughout their consumption lifecycle (i.e., the stages of acquisition, growth, retention, and win-back) or across customers' repeated journeys with the firm.

The existing empirical research on CX explored the measurement of CX from a multidimensional view; researchers have also discussed the antecedents and consequences of CX in a relatively static way and explained how one might manage CX through the multiple touchpoints/omnichannel perspective. However, there is limited empirical work that directly delineates and examines the dynamic nature of CX or touches on its dynamic management, taking into account its dynamic nature and complex conceptualization. This thesis undertakes three studies that close the dynamic gap between the conceptual and empirical research on customer experience.

Focusing on the existing customers' CX trajectories, studies 1 and 2 establish the CET framework that provides the basis for examining the dynamics of the CX trajectory at both the individual and firm levels. The CET framework rests on three foundations. First, the CX performance states are the building blocks, which represent different combinations of consumer behavior or the firm performance from the lower to higher levels. Second, these CX performance states are dynamic, evolving throughout the duration of the trajectory. Third, three major migration mechanisms, (1) the multidimensions of perceived CX (affective, cognitive, physical, social), (2) the ARCI value co-creation mechanism (activities, resources, contexts, interactions), and (3) real-world managerial actions, have dynamic effectiveness regarding the evolution of the CX trajectories.

Study 3 adds supplementary value to building the theory of the CET framework. This study helps to inform firms' online communication strategies, including which MR components are likely to have the greatest impacts and the MR components to which managers should pay particular attention if they wish to regulate their customers' emotions and manage their rating behaviors. The proposed Online CR-MR Echoverse in study 3 helps to deepen our understanding of the dynamics of the CX trajectory in several ways. First, it assesses how a relatively comprehensive set of components of MR (from the firms' side) and CR (from the customers' side) can reverberantly influence each other across the CX trajectory's duration. Second, study 3 captures the dynamic spillover effects of distinct MR components on future customers' emotions and rating behaviors and the herding effects among customers. The echoverse between firms and customers adds practical value for insights into study 1 and study 2, guiding firms on how to manage their customers' CX trajectory through managing their online CRs. Moreover, study 3 provides practical toolkits for studies 1 & 2 regarding how to improve firms' trajectories of CX performance by more widely managing the audience's online reviews. Finally, the empirical findings in study 3 provide insights into managing the dynamics of customers' emotions and rating behaviors, which echoes the foundations of the evolution and dynamic management of CX performance states in the first two studies.

6.2.2 Developing a Customer Experience Management Theory from a Dynamic Perspective: A Theory of CETs for Existing Customer Retention

Although some may argue that customer experience management, if not part of, is at least similar to/closely interrelated with the CRM streams on marketing management (e.g., Davey, 2012; Payne & Frow, 2005), we suggest that several fundamental differences must be accounted for in order to understand and dynamically execute customer experience management (CXM) strategies. To support this idea, we first describe several unique characteristics of CXM, differentiating this concept from CRM. Then, we outline evidence from both the extant literature and this thesis to discuss the implications for building and executing CXM strategies dynamically, focusing on "existing customer retention." We thus propose a theory for dynamically managing the customer experience, called "A Theory of CETs for Existing Customer Retention". The CET theory rests on three fundamental assumptions and two tenets, which are discussed as follows.

1. **Definition of the key constructs in the theory and how these differ from extant studies**

Meyer and Schwager (2007) differentiate CRM (i.e., knowing one's customers and leveraging that data) from CXM (i.e., knowing how one's customers react and behave in real-time and leveraging that data). Similarly, a growing number of researchers have alluded to CXM as the most appropriate approach for implementing an evolving marketing concept (e.g., Achrol & Kotler, 2012; Homburg et al., 2017; Webster & Lusch, 2013). Homburg et al. (2017) position CXM within the existing literature and propose that CXM entails and extends the tenets of CRM along its three main categories (cultural mindsets, strategic directions, and firm capabilities). They further propose that these extended marketing management concepts serve to implement an evolving marketing concept. Following Homburg's proposition, we contend that it is necessary to identify and recognize the contributions of these established researches on CRM as well as other interrelated marketing streams. This will enable us truly to understand and appreciate CXM as a renewed, evolving concept, that is derived from previous researchers' contributions.

2. Key assumptions/scope conditions of the theories

The proposed theory of CETs rests on three fundamental assumptions. First, the CX performance states comprise the building blocks of CET Theory. Second, the CX performances are dynamic, evolving throughout the duration of the customer experience trajectory. Third, effective CXM strategies will induce migration across the CX performance states. Dynamic customer experience management requires firms to seek out CXM strategies that effectively promote or suppress state migration as a means of enhancing their CX performance.

Assumption 1: The CX Performance States.

The CX performance states are the building blocks of the customer experience trajectory. We propose and examine the CX performance state at both the individual customer and firm levels.

However, different research contexts might cite various state variables for de-stemming the CX performance state. In this thesis, we employ the rating score, revisit intention, referral, compliments, and complaints as the CX performance state variables.

Future research might choose other variables, such as performance outcome variables (e.g., sales revenue, stock price, sales growth, share of wallet, relationship duration). Moreover, future research may also use the different dimensions of the customer experience as the state variables to comprise the CX performance state. The blend of state variables will, individually and in combination, capture the multifaceted richness of CX performance from different aspects, which might include the performance of different dimensions of customer experience, customer behavioral performance, firm business performance, and firm-customer relationship performance.

Assumption 2: The Dynamic Evolution of CX Performance States

Consumers and firms migrate or evolve dynamically across different CX performance states. Each CX performance state may express different levels of transience or stickiness. Customers/firms may gradually migrate and transition from one state to other states but may also suddenly improve or deteriorate in extreme circumstances. Some dynamic models, such as HMMs, are well suited to the task of inferring these flexible migrations between CX performance states.

Assumption 3: The Migration Mechanisms for Dynamically Managing CX Performance

The core of CXM is the provision of effective migration mechanisms that can capture customers or firms' migration paths across the CX performance states. The most effective mechanisms can be identified as CXM strategies/tools that will help firms to promote migration to higher performance states and prevent deterioration to lower ones.

Moreover, different migration mechanisms will exert distinct effects in various CX performance states. Thus, a dynamic CXM strategic perspective should focus on the differential effectiveness of CXM strategies across different CX performance states and provide managerial guidance regarding dynamic resource allocation.

3. Tenets arising from the Empirical Findings: Effective Strategies for Managing Existing (Repeat/Non-Repeat) Customers

Practical tenets arise from the differences between the repeat customers (study 1) and wider audience (study 2 and study 3) datasets, with the empirical results from the three studies informing two tenets for retaining existing customers by understanding their customer experience trajectory (CET).

Managerial Tenet 1: Existing, Repeat Customer Retention

Repeat customers can be segmented into two groups: fewer compliments with a higher engagement level and more compliments with a lower engagement level, which we call the positive-passive group and the positive-active group, respectively. For both groups, the affective dimension of CX is the most influential mechanism that helps to boost customer behavioral performance. Specifically, for the positive-active group, the cognitive and physical dimensions of CX are useful in preventing them from sinking to a lower performance state. CXM practitioners should pay particular attention to the social dimension of perceived CX since this might exert opposite effects (backfire) on the desired migration paths for both segments.

Managerial Tenet 2: Existing, Wider Audience Retention

From the firm’s perspective, not all of their existing customers are repeat ones. The CXM practitioner, who is evaluating a firm’s CX performance at the collective level, will find that their non-repeat customer base will tend to perceive the received experience in high (H) or very high (H^+) states. However, the same applies to firms that are perceived as low (L) or medium (M) experience providers, since their CX performance tends to be "sticky" in the same state for a period of time. The empirical results offer insights into the CXM strategies that managers can directly control, using these to influence the perceived CX performances. For instance, increasing the positive perceptions of a firm's activities and the positive interactions between firms and customers are useful for transitioning up the firm's CX performance. On the other hand, negative perceptions of firms' resources and negative interactions between firms and customers will reduce the firms' CX performance migration. In terms of the firms' responsive (MR) strategies toward the wider audiences’ online CR, expressing good interactions between firms and customers is the most effective strategy for regulating the wider audiences' (later customers’) positive emotions and positive rating behavior.

6.3 Conclusion

Prior to reaching our final conclusion, we wish to discuss the synergy effects generated from the three empirical studies which share much in common in terms of their methodologies, data collection and processing approaches.

The first synergy effect emerges from the integration of three perspectives of our datasets, which portray a comprehensive picture of CX dynamics from the experience receivers' perspectives, the experience providers' perspectives and from both parties' perspectives. The second synergy effect is generated through the sharing advantages of textual data among the three studies regarding how text data can be used for both the prediction and understanding of the CX dynamic phenomenon. The third synergy effect arises regarding the similar three-step process shared by the three studies. We thus provide a how-to guide, detailing the main tools for researchers and marketing practitioners, from the first step of the data collection through the web crawling technique, to the second step of data processing through texting mining and dictionary development methods, and the third step of data analysis by employing HMM and VAR modeling tools. The final synergy effect arises from the usage of HMM and VAR modeling tools. We use the HMM model to capture the dynamic nature of the CX trajectories for experience receivers in study 1 and experience providers in study 2. We employ the VAR model to depict the dynamic reverberation between the experience receivers and experience providers in study 3. These two approaches together form a relatively complete understanding of CX "dynamic" research.

Moreover, some consideration should be made regarding future research avenues. One limitation of our empirical findings is the issue of generalization. The managerial implications and takeaways generated by studies 1-3 are suitable for use in the hospitality industry but may be inapplicable to other service settings, such as banking/financial services, medical/health care services or physical product categories. One suggested area for future research would be to explore whether the observed effects extend to new research settings. In this thesis, we wrapped a dynamic CXM theory and managerial tenets to retain current/repeat customers and attract future/general customers in hospitality service settings. We predict that the empirical results would differ if physical products were involved, such as collecting repeat/non-repeat customers' reviews on Amazon.com. Another emerging issue to consider is how our findings might be extended to other service domains to see if our observed results hold true in different realms. One might predict, for example, that the results may hold true in settings related to entertainment-oriented services, such as restaurants, cinemas, or theme parks. However, they may differ in settings that provide professionally-oriented services, such as hospitals, banks, or telecommunications. In addition, we call for future research to explore our findings or test our proposed theories through experiment designs that employ lab data. The use of randomized controlled experiments could tackle the self-selection issue and endogeneity bias, allowing causal inferences to be drawn. Moreover, our findings from studies 1-3 indicate several backfire effects that operate contrary to the expected directions. For example, we invite future researchers to examine the reasons why previous social CX or the provision of explanations in previous MRs deteriorate the later CX performance. We believe that these are important and intriguing questions that merit future investigation to enrich the proposed theories and managerial tenets.

To conclude, the studies in this thesis complement and support each other and form a complete picture of existing customers' experience trajectory. This thesis closes the dynamic gap between CX conceptualization and CX empiricism across three papers. The findings depict the co-evolutionary phenomenon between customer experience and customer behavior, thereby providing an understanding of the dynamics of CX performance from both the individual and firm perspectives, and offering effective mechanisms that can help to improve CX performance dynamically. Through this thesis, we propose a theory of CET (Customer Experience Trajectory) for retaining existing customers that is based on three fundamental assumptions, which gives rise to two managerial tenets.

References

Abbott, Lawrence (1955), Quality and Competition. NY: Columbia University Press.

Achrol, R. S., & Kotler, P. (2012). Frontiers of the marketing paradigm in the third millennium. Journal of the Academy of Marketing Science, 40(1), 35-52.

Aggarwal, C. C., & Zhai, C. (2012). A survey of text classification algorithms. In Mining text data (pp. 163-222). Springer, Boston, MA.

Aggarwal, C. C., & Zhai, C. (Eds.). (2012). *Mining Text Data*. Springer Science & Business Media.

Ajzen, I., & Fishbein, M. (1977). Attitude-Behavior Relations: A Theoretical Analysis and Review of Empirical Research. *Psychological Bulletin, 84*(5), 8-918.

Anderl, E., Becker, I., Von Wangenheim, F., & Schumann, J. H. (2016). Mapping the customer journey: Lessons learned from graph-based online attribution modeling. *International Journal of Research in Marketing, 3*3(3), 457-474.

Anderson, E. T., & Simester, D. I. (2014). Reviews without a purchase: Low ratings, loyal customers, and deception. *Journal of Marketing Research, 51*(3), 249-269.

Anderson, E. W. (1998). Customer satisfaction and word of mouth. *Journal of Service Research, 1*(1), 5-17.

Anderson, E. W. (1998). Customer satisfaction and word of mouth. *Journal of Service Research*, *1*(1), 5-17.

Anderson, J. R. (1985). A series of books in psychology. Cognitive psychology and its implications (2nd ed.). New York, NY, US: WH Freeman/Times Books/Henry Holt & Co.

Anderson, P. (1986). Personality, Perceptions and Emotion-State Factors in Approach-

Avoidance Behaviors in the Store Environment. In Terence A. Shimp Et Al. (Eds.), 1986 AMA Educators' Proceedings (Pp. 35–39). Chicago: American Marketing Association

Andrews, R. L., Ansari, A., & Currim, I. S. (2002). Hierarchical Bayes Versus Finite Mixture Conjoint Analysis Models: A Comparison of Fit, Prediction, and Partworth Recovery. *Journal of Marketing Research*, *39*(1), 87-98.

Ansari, A., Mela, C. F., & Neslin, S. A. (2008). Customer channel migration. *Journal of Marketing Research, 45*(1), 60-76.
Ansari, A., Mela, C. F., & Neslin, S. A. (2008). Customer channel migration. *Journal of Marketing Research, 45*(1), 60-76.
Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, *106*(51), 21544-21549.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science*, *57*(8), 1485-1509.

Arnould, E. J., & Price, L. L. (1993). River magic: Extraordinary experience and the extended service encounter. *Journal of Consumer Research, 20*(1), 24-45.

Arnould, E. J., & Price, L. L. (1993). River Magic: Extraordinary Experience and the Extended Service Encounter. *Journal of Consumer Research*, *20*(1), 24-45.

Ascarza, E., Netzer, O., & Hardie, B. G. (2018). Some customers would rather leave without saying goodbye. *Marketing Science, 37*(1), 54-77.

Ataman, M. B., Mela, C. F., & Van Heerde, H. J. (2008). Building brands. *Marketing Science, 27*(6), 1036-1054.

Babin, B. J., Darden, W. R., & Griffin, M. (1994). Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value. *Journal of Consumer Research*, *20*(4), 644-656.

Bagdare, S., & Jain, R. (2013). Measuring retail customer experience. International *Journal of Retail & Distribution Management, 41*(10), 790-804.

Baker, A. M., Donthu, N., & Kumar, V. (2016). Investigating how word-of-mouth conversations about brands influence purchase and retransmission intentions. *Journal of Marketing Research*, *53*(2), 225-239.

Baker, J., Parasuraman, A., Grewal, D., & Voss, G. B. (2002). The influence of multiple store environment cues on perceived merchandise value and patronage intentions. *Journal of Marketing, 66*(2), 120-141.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science, 46*(4), 557-590.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science*, *46*(4), 557-590.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science*, *46*(4), 557-590.

Ballantyne, D., & Varey, R. J. (2006). Creating value-in-use through marketing interaction: the exchange logic of relating, communicating and knowing. *Marketing Theory, 6*(3), 335-348.

Ballantyne, D., & Varey, R. J. (2006). Introducing a dialogical orientation to the service-dominant logic of marketing. The service-dominant logic of marketing: Dialog, debate, and directions, 224-35.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of*

Economics, *107*(3), 797-817.

Baron, S., & Harris, K. (2008). Consumers as resource integrators. *Journal of Marketing Management, 24*(1-2), 113-130.

Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, *47*(4), 644-675.

Bart, Y., Stephen, A. T., & Sarvary, M. (2014). Which products are best suited to mobile advertising? A field study of mobile display advertising effects on consumer attitudes and intentions. *Journal of Marketing Research, 51*(3), 270-285.

Bart, Y., Stephen, A. T., & Sarvary, M. (2014). Which products are best suited to mobile advertising? A field study of mobile display advertising effects on consumer attitudes and intentions. *Journal of Marketing Research*, *51*(3), 270-285.

Bartolucci, F., Farcomeni, A., & Pennoni, F. (2014). Latent Markov models: a review of a general framework for the analysis of longitudinal data with covariates. Test, 23(3), 433-465.

Barwitz, N., & Maas, P. (2018). Understanding the omnichannel customer journey: Determinants of interaction choice. *Journal of Interactive Marketing, 43*, 116-133.

Baxendale, S., Macdonald, E. K., & Wilson, H. N. (2015). The impact of different touchpoints on brand consideration. *Journal of Retailing, 91*(2), 235-253.

Baxendale, S., Macdonald, E. K., & Wilson, H. N. (2015). The impact of different touchpoints on brand consideration. *Journal of Retailing, 91*(2), 235-253.

Bearden, W. O., & Teel, J. E. (1983). Selected determinants of consumer satisfaction and complaint reports. *Journal of Marketing Research, 20*(1), 21-28.

Bearden, W. O., & Teel, J. E. (1983). Selected Determinants of Consumer Satisfaction and Complaint Reports. *Journal of Marketing Research*, *20*(1), 21-28.

Beckers, S. F., Risselada, H., & Verhoef, P. C. (2014). Customer engagement: A new frontier in customer value management. In Handbook of service marketing research. Edward Elgar Publishing.

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology*, *24*(4), 586-607.

Berger, J., & Milkman, K. L. (2012). What makes online content viral?. *Journal of Marketing Research*, *49*(2), 192-205.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the tribes: Using text for marketing insight. *Journal of Marketing, 84*(1), 1-25.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the tribes: Using text for marketing insight. *Journal of Marketing, 84*(1), 1-25.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the tribes: Using text for marketing insight. *Journal of Marketing*, *84*(1), 1-25.

Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience. *Journal of Marketing, 66*(3), 1-17.

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. RAND *Journal of Economics, 25*(2), 242-262.

Bettencourt, L. M. (2014). The uses of big data in cities. Big Data, 2(1), 12-22.

Biedenbach, G., & Marell, A. (2010). The impact of customer experience on brand equity in a business-to-business services setting. *Journal of Brand Management, 17*(6), 446-458.

Bijmolt, Tammo H.A. and Peter C. Verhoef (2016), "Loyalty Program: Current Insights, Analytical Challenges and Emerging Trends," in Handbook of Marketing Decision Models. Berend Wierenga and Ralf van der Lans, eds. Berlin: Springer, forthcoming.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992-1026.

Bilgicer, T., Jedidi, K., Lehmann, D. R., & Neslin, S. A. (2015). Social contagion and customer adoption of new sales channels. *Journal of Retailing, 91*(2), 254-271.

Bitner, M. J. (1992). Servicescapes: The impact of physical surroundings on customers and employees. *Journal of Marketing, 56*(2), 57-71.

Bitner, M. J., Booms, B. H., & Mohr, L. A. (1994). Critical service encounters: The employee's viewpoint. *Journal of Marketing, 58*(4), 95-106.

Bitner, M. J., Booms, B. H., & Tetreault, M. S. (1990). The service encounter: diagnosing favorable and unfavorable incidents. *Journal of Marketing*, *54*(1), 71-84.

Bitner, M. J., Ostrom, A. L., & Morgan, F. N. (2008). Service blueprinting: a practical technique for service innovation. *California Management Review, 50*(3), 66-94.

Blaine, T., & Boyer, P. (2018). Origins of sinister rumors: A preference for threat-related material in the supply and demand of information. *Evolution and Human Behavior*, *39*(1), 67-75.

Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. *Journal of Marketing, 83*(2), 98-119.

Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. *Journal of Marketing, 83*(2), 98-119.

Bodine, Kerry (2013), "The Customer Experience Ecosystem," research report, Forrester Research.

Boghrati, Reihane, and Jonah Berger (2019) "Quantifying 60 Years of Misogyny in Music," working paper.

Bolton, G., Greiner, B., & Ockenfels, A. (2013). Engineering trust: reciprocity in the production of reputation information. *Management Science*, *59*(2), 265-285.

Bolton, R. N. (2011). Comment: Customer engagement: Opportunities and challenges for organizations. *Journal of Service Research, 14*(3), 272-274.

Bolton, R. N. (2016). Service excellence: creating customer experiences that build relationships. Business Expert Press.

Bolton, R. N., & Drew, J. H. (1991). A multistage model of customers' assessments of service quality and value. *Journal of Consumer Research, 17*(4), 375-384.

Bolton, R. N., & Drew, J. H. (1991). A Multistage Model of Customers' Assessments of Service Quality and Value. *Journal of Consumer Research*, *17*(4), 375-384.

Bolton, R. N., & Lemon, K. N. (1999). A dynamic model of customers' usage of services: Usage as an antecedent and consequence of satisfaction. *Journal of Marketing Research, 36*(2), 171-186.

Bolton, R. N., & Lemon, K. N. (1999). A Dynamic Model of Customers' Usage of Services: Usage as an Antecedent and Consequence of Satisfaction. *Journal of Marketing Research*, *36*(2), 171-186.

Bolton, R. N., Gustafsson, A., McColl-Kennedy, J., Sirianni, N. J., & Tse, D. K. (2014).

Small details that make big differences: a radical approach to consumption experience as a firm's differentiating strategy. *Journal of Service Management, 25*(2), 253-274.

Bolton, R. N., McColl-Kennedy, J. R., Cheung, L., Gallan, A., Orsingher, C., Witell, L., & Zaki, M. (2018). Customer experience challenges: bringing together digital, physical and social realms. *Journal of Service Management, 29*(5), 776-808.

Bolton, R., & Saxena-Iyer, S. (2009). Interactive services: a framework, synthesis and research directions. *Journal of Interactive Marketing, 23*(1), 91-104.

Bonchek, M., & France, C. (2014, May 7). Marketing Can No Longer Rely on the Funnel. Retrieved April 4, 2016, from Harvard Business Review: https://hbr.org/2014/05/marketing-can-no-longer-rely-on-the-funnel

Boulding, W., Kalra, A., Staelin, R., & Zeithaml, V. A. (1993). A dynamic process model of service quality: from expectations to behavioral intentions. *Journal of Marketing Research, 30*(1), 7-27.

Boulding, W., Kalra, A., Staelin, R., & Zeithaml, V. A. (1993). A Dynamic Process Model of Service Quality: From Expectations to Behavioral Intentions. *Journal of Marketing Research*, *30*(1), 7-27.

Brakus, J. J., Schmitt, B. H., & Zarantonello, L. (2009). Brand experience: what is it? How is it measured? Does it affect loyalty?. *Journal of Marketing, 73*(3), 52-68.

Brasel, S. A., & Gips, J. (2015). Interface psychology: touchscreens change attribute importance, decision criteria, and behavior in online choice. *Cyberpsychology, Behavior, and Social Networking, 18*(9), 534-538.

Bridges, J., & Vásquez, C. (2018). If nearly all Airbnb reviews are positive, does that make them meaningless?. *Current Issues in Tourism*, *21*(18), 2057-2075.

Brinker, Mike, Kasey Lobaugh, and Alison Paul (2012), "The Dawn of Mobile Influence: Discovering the Value of Mobile in Retail," Deloitte Digital (June) (accessed December 17, 2014), [available at http://www2.deloitte.com/content/dam/Deloitte/us/Documents/ consumer-business/us-retail-mobile-influence-factor-062712.pdf].

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research, 14*(3), 252-271.

Broniarczyk, S. M., Hoyer, W. D., & McAlister, L. (1998). Consumers' perceptions of the assortment offered in a grocery category: The impact of item reduction. *Journal of Marketing Research, 35*(2), 166-176.

Bronnenberg, B. J., Mahajan, V., & Vanhonacker, W. R. (2000). The emergence of market structure in new repeat-purchase categories: The interplay of market share and retailer distribution. *Journal of Marketing Research*, *37*(1), 16-31.

Brown, J. J., & Reingen, P. H. (1987). Social ties and word-of-mouth referral behavior. *Journal of Consumer Research*, *14*(3), 350-362.

Brynjolfsson, Erik, Yu Jeffrey Hu, and Mohammed S. Rahman (2013), "Competing in the Age of Omnichannel Retailing," *MIT Sloan Management Review, 54*(4), 23–29.

Cao, L., & Li, L. (2015). The impact of cross-channel integration on retailers' sales growth. *Journal of Retailing, 91*(2), 198-216.

Carbone, L. P., & Haeckel, S. H. (1994). Engineering customer experiences. *Marketing Management, 3*(3), 8-19.

Chaffey, D. (2016). Statistics on consumer mobile usage and adoption to inform your mobile marketing strategy mobile site design and app development. Mobile Marketing Statistics compilation: Mobile Market Analytics.

Chang, H. H., Tsai, Y. C., Wong, K. H., Wang, J. W., & Cho, F. J. (2015). The effects of response strategies and severity of failure on consumer attribution with regard to negative word-of-mouth. *Decision Support Systems, 71*(C), 48-61.

Chang, H. H., Tsai, Y. C., Wong, K. H., Wang, J. W., & Cho, F. J. (2015). The effects of response strategies and severity of failure on consumer attribution with regard to negative word-of-mouth. *Decision Support Systems*, *71*, 48-61.

Chen, W., Gu, B., Ye, Q., & Zhu, K. X. (2019). Measuring and managing the externality of managerial responses to online customer reviews. *Information Systems Research, 30*(1), 81-96.

Chen, W., Gu, B., Ye, Q., & Zhu, K. X. (2019). Measuring and managing the externality of managerial responses to online customer reviews. *Information Systems Research*, *30*(1), 81-96.

Chen, W., Wei, X., & Zhu, K. (2017). Engaging voluntary contributions in online communities: A hidden Markov model. *MIS Quarterly, 42*(1), 83-100.

Chen, W., Wei, X., & Zhu, K. X. (2018). Engaging Voluntary Contributions in Online Communities: A Hidden Markov Model. *Management Information Systems Quarterly, 42*(1), 83-100.

Chen, Y., & Xie, J. (2008). Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science*, *54*(3), 477-491.

Chen, Y., Fay, S., & Wang, Q. (2011). The role of marketing in social media: How online consumer reviews evolve. *Journal of Interactive Marketing*, *25*(2), 85-94.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43*(3), 345-354.

Chevalier, J. A., Dover, Y., & Mayzlin, D. (2018). Channels of Impact: User reviews when quality is dynamic and managers respond. *Marketing Science*, *37*(5), 688-709.

Chheda, S., Duncan, E., & Roggenhofer, S. (2019). Putting customer experience at the heart of next-generation operating models. Digital McKinsey", March, Forthcoming.

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and Utilitarian Motivations for Online Retail Shopping Behavior. *Journal of Retailing*, *77*(4), 511-535.

Chung, T. S., Rust, R. T., & Wedel, M. (2009). My mobile music: An adaptive personalization system for digital audio players. *Marketing Science, 28*(1), 52-68.

Clatworthy, S. (2011). Service innovation through touch-points: Development of an innovation toolkit for the first stages of new service development. International *Journal of Design, 5*(2), 15-28.

Cohen, A. (2007). Commitment before and after: An evaluation and reconceptualization of organizational commitment. *Human Resource Management Review, 17*(3), 336-354.

Cohen, J. B., Pham, M. T., & Andrade, E. B. (2008). The nature and role of affect in consumer behavior. *Handbook of Consumer Psychology*, *4*, 297-348.

Cohn, M. A., Mehl, M. R., & Pennebaker, J. W. (2004). Linguistic markers of psychological change surrounding September 11, 2001. *Psychological Science, 15*(10), 687-693.

Conlon, D. E., & Murry, N. M. (1996). The role of explanations in customer perceptions of corporate responses to product complaints. *The Academy of Management Journal*, *39*(4), 140-156.

Coombs, W. T. (2007). Protecting organization reputations during a crisis: The development and application of situational crisis communication theory. *Corporate reputation review*, *10*(3), 163-176.

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. McKinsey Quarterly, 3, 1-11. Retrieved from https://www.mckinseyquarterly.com/

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The Consumer Decision Journey. *Mckinsey Quarterly*, *3*(3), 96-107.

Cova, B., & Salle, R. (2008). Marketing solutions in accordance with the SD logic: Co-creating value with customer network actors. *Industrial Marketing Management, 37*(3), 270-277.

Darke, P. R., Brady, M. K., Benedicktus, R. L., & Wilson, A. E. (2016). Feeling Close from Afar: The Role of Psychological Distance in Offsetting Distrust in Unfamiliar Online Retailers. *Journal of Retailing*, *92*(3), 287-299.

Davey, N. (2012). Meet the new boss: Is customer experience management the new CRM. Retrieved July, 23, 2013.

Davidow, M. (2003). Organizational responses to customer complaints: What works and what doesn’t. *Journal of Service Research*, *5*(3), 225-250.

Dawson, S., Bloch, P. H., & Ridgway, N. (1990). Shopping motives, emotional states, and. *Journal of Retailing*, *66*(4), 408-427.

De Haan, E., Wiesel, T., & Pauwels, K. (2016). The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. *International Journal of Research in Marketing, 33*(3), 491-507.

De Haan, Evert, P.K. Kannan, Peter C. Verhoef, and Thorsten Wiesel (2015), "The Role of Mobile Devices in the Online Customer Journey," MSI Working Paper No. 15-124. Cambridge, MA: Marketing Science Institute

De Keyser, A., Lemon, K. N., Klaus, P., & Keiningham, T. L. (2015). A framework for understanding and managing the customer experience. Marketing Science Institute working paper series, 15(121), 1-48.

De Keyser, A., Schepers, J., & Konuş, U. (2015). Multichannel customer segmentation: Does the after-sales channel matter? A replication and extension. *International Journal of Research in Marketing, 32*(4), 453-456.

De Ruyter, K., Wetzels, M., Lemmink, J., & Mattson, J. (1997). The dynamics of the service delivery process: a value-based approach. *International Journal of Research in Marketing, 14*(3), 231-243.

De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing, 26*(2), 83-91.

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science, 49*(10), 1407-1424.

Dellarocas, C., & Wood, C. A. (2008). The sound of silence in online feedback: Estimating trading risks in the presence of reporting bias. *Management Science*, *54*(3), 460-476.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23-45.

Dennis, C., Joško Brakus, J., & Alamanos, E. (2013). The wallpaper matters: Digital signage as customer-experience provider at the Harrods (London, UK) department store. *Journal of Marketing Management, 29*(3-4), 338-355.

Dens, N., De Pelsmacker, P., & Purnawirawan, N. (2015). 'We (b) care' How review set balance moderates the appropriate response strategy to negative online reviews. *Journal of Service Management, 26*(3), 486-515.

Dhar, V., & Chang, E. A. (2009). Does chatter matter? The impact of user-generated content on music sales. *Journal of Interactive Marketing*, *23*(4), 300-307.

Dhebar, A. (2013). Toward a compelling customer touchpoint architecture. *Business Horizons, 56*(2), 199-205.

Dichter, E. (1966). How Word-Of-Mouth Advertising Works. *Harvard Business Review*, *44*, 147-166.

Dick, A. S., & Basu, K. (1994). Customer loyalty: toward an integrated conceptual framework. *Journal of the Academy of Marketing Science, 22*(2), 99-113.

Ding, A. W., & Li, S. (2019). Herding in the consumption and purchase of digital goods and moderators of the herding bias. *Journal of the Academy of Marketing Science*, *47*(3), 460-478.

Dorotic, M., Fok, D., Verhoef, P. C., & Bijmolt, T. H. (2011). Do vendors benefit from promotions in a multi-vendor loyalty program?. *Marketing Letters, 22*(4), 341-356.

Du, R. Y., Kamakura, W. A., & Mela, C. F. (2007). Size and share of customer wallet.

Journal of Marketing, 71(2), 94-113.

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing*, *84*(2), 233-242.

Dunning, D., Perie, M., & Story, A. (1991). Self-Serving Prototypes of Social Categories. *Journal of Personality and Social Psychology*, *61*(6), 957-968.

Dunphy, Fi (2012), "The ODEON Facebook Crisis & Edgerank," (accessed October 26, 2019), www.branded3.com/blog/theodeon-facebook-crisis-edgerank.

Dwayne, D. G., & Stephen, W. B. (1999). The loyalty ripple effect. Appreciating the full value of customers. *International Journal of Service Industry Management, 10*(3), 271-293.

Eastlick, M. A., & Feinberg, R. A. (1999). Shopping motives for mail catalog shopping. *Journal of Business Research, 45*(3), 281-290.

Edelman, D. C. (2010). Branding In The Digital Age. *Harvard Business Review*, *88*(12), 62-69.

Edelman, D. C., & Singer, M. (2015). Competing on customer journeys. *Harvard Business Review, 93*(11), 88-100.

Edvardsson, B. (2005). Service quality: beyond cognitive assessment. *Managing Service Quality, 15*(2), 127-131.

Edvardsson, B., Enquist, B., & Johnston, R. (2005). Cocreating customer value through hyperreality in the prepurchase service experience. *Journal of Service Research, 8*(2), 149-161.

Elberse, A. (2010). Bye-bye bundles: The unbundling of music in digital channels.

Journal of Marketing, 74(3), 107-123.

Emrich, O., & Verhoef, P. C. (2015). The impact of a homogenous versus a prototypical Web design on online retail patronage for multichannel providers. *International Journal of Research in Marketing, 32*(4), 363-374.

Emrich, O., Paul, M., & Rudolph, T. (2015). Shopping benefits of multichannel assortment integration and the moderating role of retailer type. *Journal of Retailing, 91*(2), 326-342.

Escalas, J. E., & Bettman, J. R. (2005). Self-Construal, Reference Groups, and Brand Meaning. *Journal of Consumer Research*, *32*(3), 378-389.

Esmark Jones, C. L., Stevens, J. L., Breazeale, M., & Spaid, B. I. (2018). Tell it like it is: The effects of differing responses to negative online reviews. *Psychology & Marketing, 35*(12), 891-901.

Ethical Corporation (2012), “Communications, Campaigns and Social Media,” (accessed September 26, 2018), www.events.ethicalcorp. com/documents/Crisis_Comms_Findings.pdf.

Ethical Corporation (2012), “Communications, Campaigns and Social Media,” (accessed September 26, 2018), www.events.ethicalcorp. com/documents/Crisis_Comms_Findings.pdf.

Evans, D., Oviatt, J., Slaymaker, J., Tapado, C., Doherty, P., Ball, A., ... & Wiley, E. (2012). An experimental study of how restaurant-owners' responses to negative reviews affect readers' intention to visit. *The Four Peaks Review*, *2*(1), 1-13.

Fader, P. S., & Hardie, B. G. (2010). Customer-base valuation in a contractual setting: The perils of ignoring heterogeneity. *Marketing Science, 29*(1), 85-93.

Fader, P. S., Hardie, B. G., & Shang, J. (2010). Customer-Base Analysis in a Discrete-Time Noncontractual Setting. *Marketing Science*, *29*(6), 1086-1108.

Falk, T., Schepers, J., Hammerschmidt, M., & Bauer, H. H. (2007). Identifying cross-channel dissynergies for multichannel service providers. *Journal of Service Research, 10*(2), 143-160.

Fayard, A. L., & DeSanctis, G. (2010). Enacting language games: the development of a sense of 'we-ness' in online forums. *Information Systems Journal*, *20*(4), 383-416.

Festinger, L., Riecken, H. W., & Schachter, S. (1956). When prophecy fails. Minneapolis, MN, US.

Fisk, R. P., Patricio, L., Lin, J. S. C., & Liang, H. Y. (2011). The influence of service environments on customer emotion and service outcomes. Managing Service Quality: An International Journal.

Fiss, P. C., & Hirsch, P. M. (2005). The discourse of globalization: Framing and sensemaking of an emerging concept. *American Sociological Review, 70*(1), 29-52.

Fornell, C., Morgeson III, F. V., & Hult, G. T. M. (2016). Stock Returns on Customer Satisfaction Do Beat the Market: Gauging The Effect of a Marketing Intangible. *Journal of Marketing*, *80*(5), 92-107.

Fornell, C., Rust, R. T., & Dekimpe, M. G. (2010). The effect of customer satisfaction on consumer spending growth. *Journal of Marketing Research, 47*(1), 28-35.

Förster, J., Liberman, N., & Friedman, R. S. (2007). Seven principles of goal activation: A systematic approach to distinguishing goal priming from priming of non-goal constructs. *Personality and Social Psychology Review*, *11*(3), 211-233.

Fossen, B. L., & Schweidel, D. A. (2019). Social TV, Advertising, and Sales: Are Social

Shows Good for Advertisers?. *Marketing Science, 38*(2), 274-295.

Fournier, S. (1998). Consumers and Their Brands: Developing Relationship Theory in Consumer Research. *Journal of Consumer Research*, *24*(4), 343-373.

Fradkin, A., Grewal, E., Holtz, D., & Pearson, M. (2015, June). Bias and reciprocity in online reviews: Evidence from field experiments on Airbnb. In *Proceedings of the Sixteenth ACM Conference on Economics and Computation* (pp. 641-641).

Frank, B., Enkawa, T., & Schvaneveldt, S. J. (2014). How do the success factors driving repurchase intent differ between male and female customers?. *Journal of the Academy of Marketing Science, 42*(2), 171-185.

Gable, S., Reis, H., Impett, E., & Asher, E. (2004). What Do You Do When Things Go Right? The Intrapersonal and Interpersonal Benefits of Sharing Positive Events. *Journal of Personality and Social Psychology*, *87*(2), 228-245.

Gahler, M., Klein, J. F., & Paul, M. (2019). Measuring customer experiences: a text-based and pictorial scale. Marketing Science Institute Working Paper Series Report, (19-119).

Gahler, M., Klein, J. F., & Paul, M. (2019). Measuring Customer Experiences: A Text-Based and Pictorial Scale. Cambridge: MSI Working Paper Series.

Gahler, M., Klein, J. F., & Paul, M. (2019). Measuring Customer Experiences: A Text-Based and Pictorial Scale.(working paper)

Galvagno, M., & Dalli, D. (2014). Theory of value co-creation: a systematic literature review. *Managing Service Quality, 24*(6), 643-683.

Garg, N., Schiebinger, L., Jurafsky, D., & Zou, J. (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of*

Sciences, 115(16), E3635-E3644.

Gefen, D., & Straub, D. (2003). Managing User Trust in B2C E-Services. *E-Service*, *2*(2), 7-24.

Gensler, S., Verhoef, P. C., & Böhm, M. (2012). Understanding consumers' multichannel choices across the different stages of the buying process. *Marketing Letters, 23*(4), 987-1003.

Gentile, C., Spiller, N., & Noci, G. (2007). How to sustain the customer experience:: An overview of experience components that co-create value with the customer. *European Management Journal, 25*(5), 395-410.

Gentile, C., Spiller, N., & Noci, G. (2007). How to sustain the customer experience: An overview of experience components that co-create value with the customer. *European Management Journal, 25*(5), 395-410.

Geyskens, I., Steenkamp, J. B. E., & Kumar, N. (1998). Generalizations about trust in marketing channel relationships using meta-analysis. *International Journal of Research in Marketing, 15*(3), 223-248.

Gijsenberg, M. J., Van Heerde, H. J., & Verhoef, P. C. (2015). Losses loom longer than gains: Modeling the impact of service crises on perceived service quality over time. *Journal of Marketing Research, 52*(5), 642-656.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, *23*(4), 545-560.

Godes, D., & Mayzlin, D. (2009). Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Science, 28*(4), 721-739.

Godes, D., & Silva, J. (2006). The dynamics of online opinion. In Working Paper.

Godes, D., & Silva, J. C. (2012). Sequential and temporal dynamics of online opinion. *Marketing Science*, *31*(3), 448-473.

Goes, P. B., Lin, M., & Au Yeung, C. M. (2014). "Popularity effect" in user-generated content: Evidence from online product reviews. *Information Systems Research*, *25*(2), 222-238.

Goh, K. Y., Heng, C. S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content. Information Systems Research, 24(1), 88-107.

Goldenberg, J., Han, S., Lehmann, D. R., & Hong, J. W. (2009). The role of hubs in the adoption process. *Journal of Marketing*, *73*(2), 1-13.

Gomez, M. I., McLaughlin, E. W., & Wittink, D. R. (2004). Customer satisfaction and retail sales performance: an empirical investigation. *Journal of Retailing, 80*(4), 265-278.

Gopalkrishnan, V., Steier, D., Lewis, H., & Guszcza, J. (2012, August). Big data, big business: bridging the gap. In Proceedings of the 1st International Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications (pp. 7-11). ACM.

Gopalkrishnan, V., Steier, D., Lewis, H., & Guszcza, J. (2012, August). Big Data, Big Business: Bridging The Gap. In *Proceedings of The 1st International Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications* (Pp. 7-11). ACM.

Grayson, K., & Ambler, T. (1999). The dark side of long-term relationships in marketing services. *Journal of Marketing Research, 36*(1), 132-141.

Grewal, D., Levy, M., & Kumar, V. (2009). Customer experience management in retailing: An organizing framework. *Journal of Retailing, 85*(1), 1-14.

Grewal, D., Levy, M., & Kumar, V. (2009). Customer experience management in retailing: an organizing framework. *Journal of Retailing, 85*(1), 1-14.

Grewal, D., Roggeveen, A. L., & Tsiros, M. (2008). The effect of compensation on repurchase intentions in service recovery. *Journal of Retailing*, *84*(4), 424-434.

Grönroos, C. (2008, December). Adopting a service business logic in relational business-to-business marketing: value creation, interaction and joint value co-creation. In Otago forum (Vol. 2, No. 9, pp. 269-287).

Grönroos, C. (2012). Conceptualising value co-creation: A journey to the 1970s and back to the future. *Journal of Marketing Management, 28*(13-14), 1520-1534.

Grönroos, C., & Voima, P. (2013). Critical service logic: making sense of value creation and co-creation. *Journal of the Academy of Marketing Science, 41*(2), 133-150.

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*(3), 281-291.

Gross, J. J., & Thompson, R. A. (2007). Emotion regulation: Conceptual foundations. In J. J. Gross (Ed.), Handbook of emotion regulation New York: Guilford Press.

Gu, B., & Ye, Q. (2014). First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management*, *23*(4), 570-582.

Gumperz, J. J., & Levinson, S. C. (1996). Introduction: Linguistic relativity re-examined. In *Rethinking linguistic relativity* (pp. 1-20). Cambridge University Press.

Gupta S., and Vajic M. (1999), "The contextual and dialectical nature of experiences", in

Fitzsimmons and Fitzsimmons (Eds.) New Service Development, Thousand Oaks, CA: Sage Publications Inc., pp35-51

Gupta, S., & Lehmann, D. R. (2003). Customers as assets. Journal of Interactive Marketing, 17(1), 9-24.

Gupta, S., Lehmann, D. R., & Stuart, J. A. (2004). Valuing customers. Journal of Marketing Research, 41(1), 7-18.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: an update. *ACM SIGKDD explorations newsletter*, *11*(1), 10-18.

Halvorsrud, R., Kvale, K., & Følstad, A. (2016). Improving Service Quality through Customer Journey Analysis. Journal of Service Theory and Practice, 26(6), 840-867.

Hamilton, R. (2016). Consumer-based strategy: Using multiple methods to generate consumer insights for strategy. *Journal of the Academy of Marketing Science, 44*(3), 281–285

Hamilton, R. Journal of the Academy of Marketing Science, 47(2), 187-191.

Hamilton, R., & Price, L. L. (2019). Consumer journeys: Developing consumer-based strategy. Journal of the Academy of Marketing Science, 47(2), 187–191.

Hancock, J. T., Landrigan, C., & Silver, C. (2007, April). Expressing emotion in text-based communication. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 929-932). ACM.

Hanssens, D. M., Pauwels, K. H., Srinivasan, S., Vanhuele, M., & Yildirim, G. (2014). Consumer attitude metrics for guiding marketing mix decisions. *Marketing Science, 33*(4), 534-550.

Hanssens, Dominique M. (2015), Empirical Generalizations About Marketing Impact, 2d ed. Cambridge, MA: Marketing Science Institute

Harmeling, C. M., Moffett, J. W., Arnold, M. J., & Carlson, B. D. (2017). Toward a theory of customer engagement marketing. *Journal of the Academy of marketing Science, 45*(3), 312-335.

Harmeling, C. M., Palmatier, R. W., Houston, M. B., Arnold, M. J., & Samaha, S. A. (2015). Transformational relationship events. *Journal of Marketing, 79*(5), 39-62.

Harmeling, C. M., Palmatier, R. W., Houston, M. B., Arnold, M. J., & Samaha, S. A. (2015). Transformational Relationship Events. *Journal of Marketing*, *79*(5), 39-62.

Heath, C., Bell, C., & Sternberg, E. (2001). Emotional selection in memes: the case of urban legends. *Journal of Personality and Social Psychology*, *81*(6), 1028-1041.

Heide, J. B. (1994). Interorganizational governance in marketing channels. *Journal of Marketing, 58*(1), 71-85.

Heinonen, K., Strandvik, T., & Voima, P. (2013). Customer dominant value formation in service. *European Business Review, 25*(2), 104-123.

Heinonen, K., Strandvik, T., Mickelsson, K. J., Edvardsson, B., Sundström, E., & Andersson, P. (2010). A customer-dominant logic of service. *Journal of Service Management, 21*(4), 531-548.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on The Internet?. *Journal of Interactive Marketing*, *18*(1), 38-52.

Herhausen, D., Binder, J., Schoegel, M., & Herrmann, A. (2015). Integrating bricks with clicks: retailer-level and channel-level outcomes of online–offline channel integration. *Journal of Retailing, 91*(2), 309-325.

Herhausen, D., Ludwig, S., Grewal, D., Wulf, J., & Schoegel, M. (2019). Detecting, preventing, and mitigating online firestorms in brand communities. *Journal of Marketing, 83*(3), 1-21.

Hertwig, R., & Ortmann, A. (2001). Experimental practices in economics: A methodological challenge for psychologists?. *Behavioral and Brain Sciences, 24*(3), 383-403.

Hess Jr, R. L., Ganesan, S., & Klein, N. M. (2003). Service failure and recovery: The impact of relationship factors on customer satisfaction. *Journal of the Academy of Marketing Science*, *31*(2), 127-145.

Hewett, K., Rand, W., Rust, R. T., & Van Heerde, H. J. (2016). Brand buzz in the echoverse. *Journal of Marketing, 80*(3), 1-24.

Hibbard, J. D., Brunel, F. F., Dant, R. P., & Iacobucci, D. (2001). Does relationship marketing age well?. *Business Strategy Review, 12*(4), 29-35.

Hibbard, J. D., Kumar, N., & Stern, L. W. (2001). Examining the Impact of Destructive Acts in Marketing Channel Relationships. *Journal of Marketing Research*, *38*(1), 45-61.

Hilken, T., de Ruyter, K., Chylinski, M., Mahr, D., & Keeling, D. I. (2017). Augmenting the eye of the beholder: exploring the strategic potential of augmented reality to enhance online service experiences. *Journal of the Academy of Marketing Science*, *45*(6), 884-905.

Hill, K., Roggeveen, A., & Grewal, D. (2015). The Impact of Service Recovery Strategies on Consumer Responses: A Conceptual Model and Meta-Analysis. *ACR North American Advances*.

Hinckley D (2015) New study: Data reveals 67% of consumers are influenced by online reviews. Moz (blog) (September 2), https://moz.com/blog/new-data-reveals-67-of-consumers-areinfluenced-by-online-reviews.

Hirschman, E. C. (1984). Experience Seeking: A Subjectivist Perspective of Consumption. *Journal of Business Research*, *12*(1), 115-136.

Ho, Y. C., Wu, J., & Tan, Y. (2017). Disconfirmation effect on online rating behavior: A structural model. *Information Systems Research*, *28*(3),

Hoch, S. J. (2002). Product experience is seductive. *Journal of Consumer Research, 29*(3), 448-454.

Hoffman, D. L., & Novak, T. P. (2018). Consumer and object experience in the internet of things: An assemblage theory approach. *Journal of Consumer Research, 44*(6), 1178-1204.

Holbrook, M. B. (1986). Aims, concepts, and methods for the representation of individual differences in esthetic responses to design features. *Journal of Consumer Research, 13*(3), 337-347.

Holbrook, M. B., & Hirschman, E. C. (1982). The experiential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research, 9*(2), 132-140.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing, 28*(2), 149-165.

Homburg, C., Ehm, L., & Artz, M. (2015). Measuring and managing consumer sentiment in an online community environment. Journal of *Marketing Research, 52*(5), 629-641.

Homburg, C., Grozdanovic, M., & Klarmann, M. (2007). Responsiveness to customers and competitors: the role of affective and cognitive organizational systems. *Journal of Marketing*, *71*(3), 18-38.

Homburg, C., Jozić, D., & Kuehnl, C. (2017). Customer experience management: toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science, 45*(3), 377-401.

Homburg, C., Steiner, V. V., & Totzek, D. (2009). Managing dynamics in a customer portfolio. *Journal of Marketing, 73*(5), 70-89.

Houston, D. M. (2016). Revisiting the relationship between attributional style and academic performance. *Journal of Applied Social Psychology, 46*(3), 192-200.

Howard, John A. And Jagdish N. Sheth. 1969. The Theory of Buyer Behavior. New York: Wiley.

Hoyer, W. D. (1984). An examination of consumer decision making for a common repeat purchase product. *Journal of Consumer Research, 11*(3), 822-829.

Hoyer, W. D., Chandy, R., Dorotic, M., Krafft, M., & Singh, S. S. (2010). Consumer cocreation in new product development. *Journal of Service Research, 13*(3), 283-296.

Hu, N., Pavlou, P. A., & Zhang, J. J. (2017). On Self-Selection Biases in Online Product Reviews. *MIS Quarterly, 41*(2), 449-471.

Hui, M. K., & Bateson, J. E. (1991). Perceived control and the effects of crowding and consumer choice on the service experience. *Journal of Consumer Research, 18*(2), 174-184.

Hui, S. K., Inman, J. J., Huang, Y., & Suher, J. (2013). The effect of in-store travel distance on unplanned spending: Applications to mobile promotion strategies. *Journal of Marketing, 77*(2), 1-16.

Hui, X., Saeedi, M., Shen, Z., & Sundaresan, N. (2016). Reputation and regulations: evidence from ebay. *Management Science*, *62*(12), 3604-3616.

Humphreys, A. (2010). Semiotic structure and the legitimation of consumption practices: The case of casino gambling. *Journal of Consumer Research, 37*(3), 490-510.

Humphreys, A., & Wang, R. J. H. (2017). Automated text analysis for consumer research. *Journal of Consumer Research, 44*(6), 1274-1306.

Humphreys, A., & Wang, R. J. H. (2018). Automated text analysis for consumer research. *Journal of Consumer Research*, *44*(6), 1274-1306.

Hung, W. L., Lee, Y. J., & Huang, P. H. (2016). Creative Experiences, Memorability and Revisit Intention in Creative Tourism. *Current Issues in Tourism*, *19*(8), 763-770.

Hunneman, A., Verhoef, P. C., & Sloot, L. M. (2015). The impact of consumer confidence on store satisfaction and share of wallet formation. *Journal of Retailing, 91*(3), 516-532.

Husson, Thomas, Julie A. Ask, Carrie Johnson, Melissa Parrish, and Emily Kwan (2014), "Predictions 2014: Mobile Trends for Marketers," research report, Forrester Research.

Iglesias, O., Singh, J. J., & Batista-Foguet, J. M. (2011). The role of brand experience and affective commitment in determining brand loyalty. *Journal of Brand Management,* *18*(8), 570-582.

Intille, S. S. (2006, June). The goal: smart people, not smart homes. In Proceedings of ICOST2006: The International Conference on Smart Homes and Health Telematics. Amsterdam: IOS Press (pp. 3-6).

Ireland, M. E., & Pennebaker, J. W. (2010). Language style matching in writing: Synchrony in essays, correspondence, and poetry. *Journal of Personality and Social Psychology*, *99*(3), 549-571.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing?. *Journal of Personality and Social Psychology, 79*(6), 995.

Jap, S. D., & Anderson, E. (2007). Testing a life-cycle theory of cooperative interorganizational relationships: Movement across stages and performance. *Management Science, 53*(2), 260-275.

Jap, S. D., & Ganesan, S. (2000). Control mechanisms and the relationship life cycle: Implications for safeguarding specific investments and developing commitment. *Journal of Marketing Research, 37*(2), 227-245.

Jiang, Z., & Benbasat, I. (2004). Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. *Journal of Management Information Systems, 21*(3), 111-147.

Johnen, M., & Schnittka, O. (2020). Changing consumers' minds at the point of sale: price discounts vs. in-store advertising. *Marketing Letters,* 1-23.

Johnson, M. D., & Selnes, F. (2004). Customer Portfolio Management: Toward A Dynamic Theory of Exchange Relationships. *Journal of Marketing*, *68*(2), 1-17.

Johnson, M. D., Herrmann, A., & Huber, F. (2006). The evolution of loyalty intentions.

Journal of Marketing, 70(2), 122-132.

Jones, T. O., & Sasser, W. E. (1995). Why satisfied customers defect. Harvard business Review, 73(6), 88-89

Kamakura, W. A., & Russell, G. J. (1989). A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research*, *26*(4), 379-390.

Kannan, P. K. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing, 34*(1), 22-45.

Kappe, E., Blank, A. S., & Desarbo, W. S. (2018). A Random Coefficients Mixture Hidden Markov Model for Marketing Research. *International Journal of Research in Marketing*, *35*(3), 415-431.

Keiningham, T., Ball, J., Benoit, S., Bruce, H. L., Buoye, A., Dzenkovska, J., ... & Zaki, M. (2017). The interplay of customer experience and commitment. *Journal of Services Marketing, 31*(2), 148-160.

Kelley, S. W., & Davis, M. A. (1994). Antecedents to customer expectations for service recovery. *Journal of the Academy of Marketing Science*, *22*(1), 52-61.

Keynes, J. M. (1936). The General Theory of Employment, Interest and Money (London, 1936). Keynes. The General Theory of Employment, Interest and Money1936.

Kim, H., Suh, K. S., & Lee, U. K. (2013). Effects of collaborative online shopping on shopping experience through social and relational perspectives. *Information & Management, 50*(4), 169-180.

Kim, J. H., Ritchie, J. R., & Tung, V. W. S. (2010). The Effect of Memorable Experience on Behavioral Intentions in Tourism: A Structural Equation Modeling

Approach. *Tourism Analysis*, *15*(6), 637-648.

Kim, M. K., Park, M. C., & Jeong, D. H. (2004). The effects of customer satisfaction and switching barrier on customer loyalty in Korean mobile telecommunication services. *Telecommunications Policy*, *28*(2), 145-159.

Kim, W. G., Lim, H., & Brymer, R. A. (2015). The effectiveness of managing social media on hotel performance. *International Journal of Hospitality Management*, *44*, 165-171.

Klaus, P. (2015). Customer Experience: The Origins and Importance for Your Business. In Measuring Customer Experience (pp. 1-21). Palgrave Macmillan, London.

Klaus, P. P., & Maklan, S. (2013). Towards a better measure of customer experience. *International Journal of Market Research, 55*(2), 227-246.

Klaus, P., & Maklan, S. (2011). Bridging the gap for destination extreme sports: A model of sports tourism customer experience. *Journal of Marketing Management, 27*(13-14), 1341-1365.

Klaus, P., & Maklan, S. (2012). EXQ: A Multiple-Item Scale for Assessing Service Experience. *Journal of Service Management*, *23*(1), 5-33.

Klaus, P., Edvardsson, B., & Maklan, S. (2012, May). Developing a typology of customer experience management practice–from preservers to vanguards. In 12th International Research Conference in Service Management, La Londe les Maures, France.

Klesse, A. K., Levav, J., & Goukens, C. (2015). The effect of preference expression modality on self-control. *Journal of Consumer Research, 42*(4), 535-550.

Ko, E., Kim, E. Y., & Lee, E. K. (2009). Modeling consumer adoption of mobile shopping for fashion products in Korea. *Psychology & Marketing, 26*(7), 669-687.

Ko□ka, K. (1935). Principles of gestalt psychology, New York: Harcourt Brace.

Koehler, W. 1938 The Place of Value in A World of Facts New York: Norton.

Koffka, K. (1935). Principles of Gestalt Psychology. London: Routledge.

Konuş, U., Neslin, S. A., & Verhoef, P. C. (2014). The effect of search channel elimination on purchase incidence, order size and channel choice. *International Journal of Research in Marketing, 31*(1), 49-64.

Konuş, U., Verhoef, P. C., & Neslin, S. A. (2008). Multichannel shopper segments and their covariates. *Journal of Retailing, 84*(4), 398-413.

Kotler, Philip & Kevin Lane Keller. 2012. Marketing Management, 14e, Global Edition, Pearson Educational Limited, England

Kowalski, R. M. (1996). Complaints and complaining: functions, antecedents, and consequences. *Psychological Bulletin*, *119*(2), 179-196.

Kozlenkova, I. V., Palmatier, R. W., Fang, E., Xiao, B., & Huang, M. (2017). Online relationship formation. *Journal of Marketing, 81*(3), 21-40.

Krallinger, M., Hirschman, L., & Valencia, A. (2008). Current Use of Text Mining and Literature Search Systems for Genome Sciences. *Genome Biology*, *9*(Suppl 2), S8.

Kranzbühler, A. M., Kleijnen, M. H., Morgan, R. E., & Teerling, M. (2018). The multilevel nature of customer experience research: an integrative review and research agenda. *International Journal of Management Reviews*, *20*(2), 433-456.

Kranzbühler, A. M., Zerres, A., Kleijnen, M. H. P., & Verlegh, P. W. J. (2020). Beyond valence: a meta-analysis of discrete emotions in firm-customer encounters. *Journal of the Academy of Marketing Science*, *48*(3), 478-498.

Kuehnl, C., Jozic, D., & Homburg, C. (2019). Effective customer journey design:

consumers' conception, measurement, and consequences. *Journal of the Academy of Marketing Science, 47*(3), 551-568.

Kumar, N., Qiu, L., & Kumar, S. (2018). Exit, voice, and response on digital platforms: An empirical investigation of online management response strategies. *Information Systems Research, 29*(4), 849-870.

Kumar, V., & Shah, D. (2009). Expanding the role of marketing: from customer equity to market capitalization. *Journal of Marketing, 73*(6), 119-136.

Kumar, V., Sriram, S., Luo, A., & Chintagunta, P. K. (2011). Assessing the effect of marketing investments in a business marketing context. *Marketing Science, 30*(5), 924-940.

Kumar, V., Umashankar, N., Kim, K. H., & Bhagwat, Y. (2014). Assessing the influence of economic and customer experience factors on service purchase behaviors. *Marketing Science, 33*(5), 673-692.

LaBarbera, P. A., & Mazursky, D. (1983). A longitudinal assessment of consumer satisfaction/dissatisfaction: the dynamic aspect of the cognitive process. *Journal of Marketing Research, 20*(4), 393-404.

Labarbera, P. A., & Mazursky, D. (1983). A Longitudinal Assessment of Consumer Satisfaction/Dissatisfaction: The Dynamic Aspect of The Cognitive Process. *Journal of Marketing Research*, *20*(4), 393-404.

Langston, C. (1994). Capitalizing On and Coping With Daily-Life Events: Expressive Responses to Positive Events. *Journal of Personality and Social Psychology*, *67*(6), 1112-1125.

Lappas, T., Sabnis, G., & Valkanas, G. (2016). The impact of fake reviews on online visibility: A vulnerability assessment of the hotel industry. *Information Systems Research, 27*(4), 940-961.

Lavidge, R. J., & Steiner, G. A. (1961). A Model for Predictive Measurements of Advertising Effectiveness. *Journal of Marketing*, *25*(6), 59-62.

Lee, S. M., Lee, D., & Kang, C. Y. (2012). The impact of high-performance work systems in the health-care industry: employee reactions, service quality, customer satisfaction, and customer loyalty. *The Service Industries Journal, 32*(1), 17-36.

Lee, T. Y., & Bradlow, E. T. (2011). Automated marketing research using online customer reviews. *Journal of Marketing Research, 48*(5), 881-894.

Lee, Y. J., Hosanagar, K., & Tan, Y. (2015). Do I follow my friends or the crowd? Information cascades in online movie ratings. *Management Science*, *61*(9), 2241-2258.

Leeflang, P. S., Spring, P. N., Van Doorn, J., & Wansbeek, T. (2013). Identifying the direct mail-prone consumer. *Journal of Global Scholars of Marketing Science, 23*(2), 175-195.

Leeflang, P. S., Verhoef, P. C., Dahlström, P., & Freundt, T. (2014). Challenges and solutions for marketing in a digital era. *European Management Journal, 32*(1), 1-12.

Leeflang, P. S., Wittink, D. R., Wedel, M., & Naert, P. A. (2013). Building models for marketing decisions (Vol. 9). Springer Science & Business Media.

Lehmann, D. R., McAlister, L., & Staelin, R. (2011). Sophistication in research in marketing. *Journal of Marketing, 75*(4), 155-165.

Lemke, A. A., Wu, J. T., Waudby, C., Pulley, J., Somkin, C. P., & Trinidad, S. B. (2010). Community engagement in biobanking: Experiences from the eMERGE Network.

Genomics, *Society and Policy, 6*(3), 50.

Lemke, F., Clark, M., & Wilson, H. (2011). Customer experience quality: an exploration in business and consumer contexts using repertory grid technique. *Journal of the Academy of Marketing Science, 39*(6), 846-869.

Lemon, K. N., & Verhoef, P. C. (2016). Understand ing customer experience throughout the customer journey. *Journal of Marketing, 80*(6), 69-96.

Lemon, K. N., & Wangenheim, F. V. (2009). The reinforcing effects of loyalty program partnerships and core service usage: a longitudinal analysis. *Journal of Service Research, 11*(4), 357-370.

Lervik-Olsen, L., van Oest, R., & Verhoef, P. C. (2015). When Is Customer Satisfaction 'Locked'? A Longitudinal Analysis of Satisfaction Stickiness. *BI Norwegian Business School*.

Lervik-Olsen, Line, Rutger van Oest, and Peter C. Verhoef (2015). "When Is Customer Satisfaction 'Locked'? A Longitudinal Analysis of Satisfaction Stickiness," working paper, BI Norwegian Business School

Levy, S. E., Duan, W., & Boo, S. (2013). An analysis of one-star online reviews and responses in the Washington, DC, lodging market. Cornell Hospitality Quarterly, 54(1), 49-63.

Levy, S. E., Duan, W., & Boo, S. (2013). An analysis of one-star online reviews and responses in the Washington, DC, lodging market. *Cornell Hospitality Quarterly*, *54*(1), 49-63.

Lewis, B. R., & McCann, P. (2004). Service failure and recovery: evidence from the hotel industry. *International Journal of Contemporary Hospitality Management*, *16*(1), 6-

17.

Li, H., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. *Journal of Marketing Research, 51*(1), 40-56.

Li, S., Sun, B., & Montgomery, A. L. (2011). Cross-selling the right product to the right customer at the right time. *Journal of Marketing Research, 48*(4), 683-700.

Li, X., & Hitt, L. M. (2008). Self-selection and information role of online product reviews. *Information Systems Research, 19*(4), 456-474.

Libai, B., Bolton, R., Bügel, M. S., De Ruyter, K., Götz, O., Risselada, H., & Stephen, A. T. (2010). Customer-to-customer interactions: broadening the scope of word of mouth research. *Journal of Service Research, 13*(3), 267-282.

Lin, A., Gregor, S., & Ewing, M. (2008). Developing a scale to measure the enjoyment of web experiences. *Journal of Interactive Marketing, 22*(4), 40-57.

Litterman, R. B. (1986). Forecasting with Bayesian vector autoregressions—five years of experience. *Journal of Business & Economic Statistics*, *4*(1), 25-38.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing, 70*(3), 74-89.

Lo, S. C. (2012). A Study of Relationship Marketing on Customer Satisfaction. *Journal of Social Sciences*, *8*(1), 91-94.

Luca, M. 2011. Reviews, reputation, and revenue: The case of Yelp.com. Harvard Business School NOM Unit Working Paper 12-016, 1-40. http://ssrn.com/abstract=1928601

Ludwig, S., & de Ruyter, K. (2016). Decoding social media speak: developing a speech act theory research agenda. *Journal of Consumer Marketing, 33*(2), 124-134.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, *77*(1), 87-103.

Luo, A., & Kumar, V. (2013). Recovering hidden buyer–seller relationship states to measure the return on marketing investment in business-to-business markets. *Journal of Marketing Research, 50*(1), 143-160.

Lusch, R. F., & Vargo, S. L. (2006). Service-dominant logic: reactions, reflections and refinements. *Marketing Theory, 6*(3), 281-288.

Ma, L., Sun, B., & Kekre, S. (2015). The Squeaky Wheel Gets the Grease—An empirical analysis of customer voice and firm intervention on Twitter. *Marketing Science, 34*(5), 627-645.

Macdonald, E. K., Kleinaltenkamp, M., & Wilson, H. N. (2016). How business customers judge solutions: Solution quality and value in use. *Journal of Marketing, 80*(3), 96-120.

Macdonald, E., Wilson, H. N., & Konus, U. (2012). Better customer insight-in real time (Vol. 90). Harvard Business School Publishing.

MacKenzie, S. B., & Lutz, R. J. (1989). An empirical examination of the structural antecedents of attitude toward the ad in an advertising pretesting context. *Journal of Marketing, 53*(2), 48-65.

Maglio, P. P., Vargo, S. L., Caswell, N., & Spohrer, J. (2009). The service system is the basic abstraction of service science. *Information Systems and e-business Management, 7*(4), 395-406.

Maklan, S., & Klaus, P. (2011). Customer experience: are we measuring the right things?. *International Journal of Market Research, 53*(6), 771-772.

Manchanda, P., Dubé, J. P., Goh, K. Y., & Chintagunta, P. K. (2006). The effect of banner advertising on internet purchasing. *Journal of Marketing Research, 43*(1), 98-108.

Manchanda, P., Packard, G., & Pattabhiramaiah, A. (2015). Social dollars: The economic impact of customer participation in a firm-sponsored online customer community. *Marketing Science, 34*(3), 367-387.

Mano, H., & Oliver, R. L. (1993). Assessing the Dimensionality and Structure of The Consumption Experience: Evaluation, Feeling, and Satisfaction. *Journal of Consumer Research*, *20*(3), 451-466.

Marcus, A. A., & Goodman, R. S. (1991). Victims and shareholders: The dilemmas of presenting corporate policy during a crisis. *Academy of Management Journal*, *34*(2), 281-305.

Marr, B. (2017). Data strategy: How to profit from a world of big data, analytics and the internet of things. Kogan Page Publishers.

Marr, B. (2017). The complete beginner's guide to big data in 2017. In Forbes. Retrieved on. September 5, 2017 from https://www.forbes.
com/sites/bernardmarr/2017/03/14/the

Marriott, H. R., & Williams, M. D. (2018, May). Enhancing the Customer Experience: Understanding UK Consumers' M-Shopping Adoption Intention. In Academy of Marketing Science Annual Conference (pp. 141-150). Springer, Cham.

Massara, F., Melara, R. D., & Liu, S. S. (2014). Impulse versus opportunistic purchasing during a grocery shopping experience. *Marketing letters, 25*(4), 361-372.

Mathwick, C., Malhotra, N., & Rigdon, E. (2001). Experiential Value: Conceptualization, Measurement and Application in The Catalog and Internet Shopping Environment. *Journal of Retailing*, *77*(1), 39-56.

Maxham III, J. G., & Netemeyer, R. G. (2002). A longitudinal study of complaining customers' evaluations of multiple service failures and recovery efforts. *Journal of Marketing*, *66*(4), 57-71.

McAlexander, J. H., Schouten, J. W., & Koenig, H. F. (2002). Building brand community. *Journal of Marketing, 66*(1), 38-54.

McColl-Kennedy, J. R., Hogan, S. J., Witell, L., & Snyder, H. (2017). Cocreative customer practices: Effects of health care customer value cocreation practices on well-being. *Journal of Business Research, 70*(C), 55-66.

McColl-Kennedy, J. R., Vargo, S. L., Dagger, T. S., Sweeney, J. C., & Kasteren, Y. V. (2012). Health care customer value cocreation practice styles. *Journal of Service Research, 15*(4), 370-389.

McColl-Kennedy, J. R., Zaki, M., Lemon, K. N., Urmetzer, F., & Neely, A. (2019). Gaining customer experience insights that matter. *Journal of Service Research, 22*(1), 8-26.

McCollough, M. A., Berry, L. L., & Yadav, M. S. (2000). An empirical investigation of customer satisfaction after service failure and recovery. *Journal of Service Research*, *3*(2), 121-137.

McQuarrie, E. F., Miller, J., & Phillips, B. J. (2013). The megaphone effect: Taste and audience in fashion blogging. *Journal of Consumer Research*, *40*(1), 136-158.

Melis, K., Campo, K., Breugelmans, E., & Lamey, L. (2015). The impact of the multichannel retail mix on online store choice: does online experience matter?. *Journal of Retailing, 91*(2), 272-288.

Mende, M., Scott, M. L., & Bolton, L. E. (2018). All That Glitters Is Not Gold: The Penalty Effect of Conspicuous Consumption in Services and How It Changes With Customers and Contexts. *Journal of Service Research, 21*(4), 405-420.

Meuter, M. L., Ostrom, A. L., Bitner, M. J., & Roundtree, R. (2003). The influence of technology anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research, 56*(11), 899-906.

Meyer, C., & Schwager, A. (2007). Understanding Customer Experience. *Harvard Business Review*, *85*(2), 116-126.

Meyer, D., Hornik, K., & Feinerer, I. (2008). Text mining infrastructure in R. *Journal of Statistical Software, 25*(5), 1-54.

Meyer, D., Hornik, K., & Feinerer, I. (2008). Text Mining Infrastructure In R. *Journal of Statistical Software*, *25*(5), 1-54.

Michalek, J. J., Ebbes, P., Adigüzel, F., Feinberg, F. M., & Papalambros, P. Y. (2011). Enhancing Marketing with Engineering: Optimal Product Line Design for Heterogeneous Markets. *International Journal of Research in Marketing*, *28*(1), 1-12.

Mittal, V., Huppertz, J. W., & Khare, A. (2008). Customer complaining: the role of tie strength and information control. *Journal of Retailing*, *84*(2), 195-204.

Mittal, V., Kumar, P., & Tsiros, M. (1999). Attribute-level performance, satisfaction, and behavioral intentions over time: a consumption-system approach. *Journal of Marketing, 63*(2), 88-101.

Moe, W. W., & Schweidel, D. A. (2012). Online product opinions: Incidence, evaluation, and evolution. *Marketing Science*, *31*(3), 372-386.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444-456.

Mogenson, David (2015), “I Want-to-Do Moments: From Home to Beauty,” Think with Google, [available at https://www. thinkwithgoogle.com/articles/i-want-to-do-micro-moments.html].

Mogilner, C., Kamvar, S. D., & Aaker, J. (2011). The shifting meaning of happiness. *Social Psychological and Personality Science, 2*(4), 395-402.

Montoya, R., Netzer, O., & Jedidi, K. (2010). Dynamic allocation of pharmaceutical detailing and sampling for long-term profitability. *Marketing Science, 29*(5), 909-924.

Moon, S., & Kamakura, W. A. (2017). A picture is worth a thousand words: Translating product reviews into a product positioning map. *International Journal of Research in Marketing, 34*(1), 265-285.

Moon, S., Park, Y., & Kim, Y. S. (2014). The impact of text product reviews on sales. *European Journal of Marketing*, *48*(11), 2176-2197.

Moore, S., Packard, G., & McFerran, B. (2012). Do words speak louder than actions? Firm language in customer service interactions. *University of Alberta, Working Paper*.

Nair, H. S., Manchanda, P., & Bhatia, T. (2010). Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *Journal of Marketing Research*, *47*(5), 883-895.

Nambisan, S., & Baron, R. A. (2007). Interactions in virtual customer environments: Implications for product support and customer relationship management. *Journal of Interactive Marketing, 21*(2), 42-62.

Nambisan, S., & Nambisan, P. (2008). How to Profit from a Better¿ Virtual Customer Environment¿. *MIT Sloan Management Review, 49*(3), 53-61.

Neslin, S. A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M. L., Thomas, J. S., & Verhoef, P. C. (2006). Challenges and opportunities in multichannel customer management. *Journal of Service Research, 9*(2), 95-112.

Netzer, C., Franken, T., Mauss, F., Seidel, L., Lehtiniemi, H., & Kulzer, A. C. (2018). Numerical analysis of the impact of water injection on combustion and thermodynamics in a gasoline engine using detailed chemistry. SAE International *Journal of Engines, 11*(6), 1151-1166.

Netzer, O., Ebbes, P., & Bijmolt, T. H. (2017). Hidden Markov Models in Marketing. In *Advanced Methods for Modeling Markets* (Pp. 405-449). Springer, Cham.

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science, 3*1(3), 521-543.

Netzer, O., Lattin, J. M., & Srinivasan, V. (2008). A hidden Markov model of customer relationship dynamics. *Marketing Science, 27*(2), 185-204.

Netzer, O., Lemaire, A., & Herzenstein, M. (2019). When words sweat: Identifying signals for loan default in the text of loan applications. *Journal of Marketing Research, 56*(6), 960-980.

Newall-Legner, Ruby, “Understanding Customers”, https://www.infinitcontact.com/blog/20- customer-service-statistics-you-cant-and-shouldnt-ignore/ (Accessed September 14, 2018)

Ng, I. C., Parry, G., Smith, L., & Maull, R. (2010). Value co-creation in complex engineering service systems: Conceptual foundations. Univ., Business School.

Ngobo, P. V. (2017). The trajectory of customer loyalty: an empirical test of Dick and Basu's loyalty framework. *Journal of the Academy of Marketing Science, 45*(2), 229-250.

Ngobo, P. V. (2017). The Trajectory Of Customer Loyalty: An Empirical Test of Dick And Basu's Loyalty Framework. *Journal of the Academy of Marketing Science*, *45*(2), 229-250.

Nijs, V. R., Srinivasan, S., & Pauwels, K. (2007). Retail-price drivers and retailer profits. *Marketing Science*, *26*(4), 473-487.

Normann, R., & Ramirez, R. (1994). Designing Interactive Strategy: From Value Chain to Value Constellation, Chichester-New York, Wiley.

Novak, T. P., & Hoffman, D. L. (2019). Relationship journeys in the internet of things: a new framework for understanding interactions between consumers and smart objects. *Journal of the Academy of Marketing Science, 47*(2), 216-237.

Novak, T. P., Hoffman, D. L., & Yung, Y. F. (2000). Measuring the customer experience in online environments: A structural modeling approach. *Marketing Science, 19*(1), 22-42.

Ofir, C., & Simonson, I. (2007). The effect of stating expectations on customer satisfaction and shopping experience. *Journal of Marketing Research, 44*(1), 164-174.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research, 17*(4), 460-469.

Oliver, R. L. (1999). Whence consumer loyalty?. *Journal of Marketing, 63*(4_suppl1), 33-44.

Oliver, R. L., & DeSarbo, W. S. (1988). Response determinants in satisfaction judgments. *Journal of Consumer Research, 14*(4), 495-507.

Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. International *Journal of Research in Marketing, 29*(3), 221-234.

Ordenes, F. V., Theodoulidis, B., Burton, J., Gruber, T., & Zaki, M. (2014). Analyzing customer experience feedback using text mining: A linguistics-based approach. *Journal of Service Research, 17*(3), 278-295.

Ostrom, A. L., Bitner, M. J., Brown, S. W., Burkhard, K. A., Goul, M., Smith-Daniels, V., ... & Rabinovich, E. (2010). Moving forward and making a difference: research priorities for the science of service. *Journal of Service Research, 13*(1), 4-36.

Ott, N., Ziai, R., & Meurers, D. (2012). Creation and analysis of a reading comprehension exercise corpus: Towards evaluating meaning in context. In Multilingual Corpora and Multilingual Corpus Analysis (pp. 47-69). John Benjamins.

Ou, C. X., Pavlou, P. A., & Davison, R. M. (2014). Swift guanxi in online marketplaces: The role of computer-mediated communication technologies. *MIS Quarterly, 38*(1), 209-230.

Packard, G., & Wooten, D. B. (2013). Compensatory knowledge signaling in consumer word-of-mouth. *Journal of Consumer Psychology*, *23*(4), 434-450.

Packard, G., Gershoff, A., & Wooten, D. (2012). Is immodesty a vice when sharing advice? Consumer responses to self-enhancing sources of word-of-mouth information. In *University of Michigan Work*

Packard, G., Moore, S. G., & McFerran, B. (2014). How can "I" help "You"? the impact of personal pronoun use in customer-firm agent interactions. *Marketing Science Institute Research Report*, 14-110.

Padgett, D., & Allen, D. (1997). Communicating experiences: A narrative approach to creating service brand image. *Journal of advertising, 26*(4), 49-62.

Palmatier, R. W., Dant, R. P., Grewal, D., & Evans, K. R. (2006). Factors influencing the effectiveness of relationship marketing: A meta-analysis. *Journal of Marketing, 70*(4), 136-153.

Palmatier, R. W., Houston, M. B., Dant, R. P., & Grewal, D. (2013). Relationship velocity: toward a theory of relationship dynamics. *Journal of Marketing, 77*(1), 13-30.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing, 64*(1), 12-40.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of expectations as a comparison standard in measuring service quality: implications for further research. *Journal of Marketing, 58*(1), 111-124.

Park, J., Gu, B., & Lee, H. (2012). The relationship between retailer-hosted and third-party hosted WOM sources and their influence on retailer sales. *Electronic Commerce Research and Applications*, *11*(3), 253-261.

Park, S. Y., & Allen, J. P. (2013). Responding to online reviews: Problem solving and engagement in hotels. *Cornell Hospitality Quarterly*, *54*(1), 64-73.

Parsons, T. (1934). Some reflections on "The nature and significance of economics". *The Quarterly Journal of Economics, 48*(3), 511-545.

Patrício, L., Fisk, R. P., & Falcão e Cunha, J. (2008). Designing multi-interface service experiences: The service experience blueprint. *Journal of Service Research, 10*(4), 318-334.

Patrício, L., Fisk, R. P., Falcão e Cunha, J., & Constantine, L. (2011). Multilevel service design: from customer value constellation to service experience blueprinting. *Journal of Service Research, 14*(2), 180-200.

Pauwels, Koen, Zeynep Aksehirli, and Andrew Lackman (2016), "Like the Ad or the Brand? Marketing Stimulates Different Electronic Word-of-Mouth Content to Drive Online and Offline Performance," International Journal of Research in Marketing, forthcoming [DOI: doi:10.1016/j.ijresmar.2016.01.005]

Payne, A. F., Storbacka, K., & Frow, P. (2008). Managing the co-creation of value. *Journal of the Academy of Marketing Science, 36*(1), 83-96.

Payne, A., & Frow, P. (2005). A strategic framework for customer relationship management. *Journal of Marketing, 69*(4), 167-176.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*(Oct), 2825-2830.

Peladeau, N. (2016), WordStat: Content Analysis Module for SIMSTAT. Montreal, Canada: Provalis Research

Pennebaker, J. W. (2011). The secret life of pronouns. New Scientist, 211(2828), 42-45.

Pennebaker, J. W., & Francis, M. E. (1996). Cognitive, emotional, and language processes in disclosure. *Cognition & Emotion*, *10*(6), 601-626.

Pennebaker, J. W., Booth, R. J., Boyd, R. L., & Francis, M. E. (2015). LIWC 2015 Operator's Manual.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The Development and Psychometric Properties of LIWC2015.

Perreault Jr, W. D., & Leigh, L. E. (1989). Reliability of nominal data based on qualitative judgments. *Journal of Marketing Research, 26*(2), 135-148.

Peters, K., & Kashima, Y. (2007). From social talk to social action: shaping the social triad with emotion sharing. *Journal of Personality and Social Psychology*, *93*(5), 780-797.

Pfeifer, P. E., & Farris, P. W. (2004). The elasticity of customer value to retention: The duration of a customer relationship. *Journal of Interactive Marketing, 18*(2), 20-31.

Pieters, R., Baumgartner, H., & Allen, D. (1995). A means-end chain approach to consumer goal structures. *International Journal of Research in Marketing, 12*(3), 227-244.

Pine, B. J., Pine, J., & Gilmore, J. H. (1999). The experience economy: Work is theatre & every business a stage. Harvard Business Press.

Pine, I. I., & Gilmore, J. H. (1998). Welcome to the experience economy. *Harvard Business Review, 76*(4), 97-105.

Pinker, S. (1997), How The Mind Works. New York: Norton.

Pinker, S. (1997). How the Mind Works. London: Allen Lane. The Penguin Press. Pinker, S., & P. Bloom (1990). Natural language and natural selection. *Behavioural and Brain Sciences, 13*, 707-784.

Prahalad, C. K., & Ramaswamy, V. (2000). Co-opting customer competence. *Harvard Business Review, 78*(1), 79-90.

Prahalad, C. K., & Ramaswamy, V. (2003). The new frontier of experience innovation. *MIT Sloan Management Review, 44*(4), 12-19

Prahalad, C. K., & Ramaswamy, V. (2004). Co-creation experiences: The next practice in value creation. *Journal of Interactive Marketing, 18*(3), 5-14.

Proserpio, D., & Zervas, G. (2017). Online reputation management: Estimating the impact of management responses on consumer reviews. *Marketing Science, 36*(5), 645-665.

Provan, K. G., & Kenis, P. (2008). Modes of network governance: Structure, management, and effectiveness. *Journal of Public Administration Research and Theory, 18*(2), 229-252.

Puccinelli, N. M., Goodstein, R. C., Grewal, D., Price, R., Raghubir, P., & Stewart, D. (2009). Customer experience management in retailing: understanding the buying process. *Journal of Retailing, 85*(1), 15-30.

Qin, L. (2011). Word-of-blog for movies: A predictor and an outcome of box office revenue?. *Journal of Electronic Commerce Research*, *12*(3), 187.

Ramani, G., & Kumar, V. (2008). Interaction orientation and firm performance. *Journal of Marketing, 72*(1), 27-45.

Rapp, A., Baker, T. L., Bachrach, D. G., Ogilvie, J., & Beitelspacher, L. S. (2015). Perceived customer showrooming behavior and the effect on retail salesperson self-efficacy and performance. *Journal of Retailing, 91*(2), 358-369.

Rawson, A., Duncan, E., & Jones, C. (2013). The truth about customer experience.

Harvard Business Review, 91(9), 90-98.

Rego, L. L., Morgan, N. A., & Fornell, C. (2013). Reexamining the market share–customer satisfaction relationship. *Journal of Marketing, 77*(5), 1-20.

Reichheld, F. F., & Sasser, W. E. (1990). Zero defeofions: Quoliiy comes to services. *Harvard Business Review, 68*(5), 105-111.

Reinartz, W. J., & Kumar, V. (2000). On the profitability of long-life customers in a noncontractual setting: An empirical investigation and implications for marketing. *Journal of Marketing, 64*(4), 17-35.

Reinartz, W. J., & Kumar, V. (2003). The impact of customer relationship characteristics on profitable lifetime duration. *Journal of Marketing*, *67*(1), 77-99.

Resnick, P., & Zeckhauser, R. (2002). Trust among strangers in internet transactions: Empirical analysis of ebay's reputation system. *The Economics of the Internet and E-commerce, 11*(2), 23-25.

Rime, B., Mesquita, B., Boca, S., & Philippot, P. (1991). Beyond the emotional event: Six studies on the social sharing of emotion. *Cognition & Emotion*, *5*(5-6), 435-465.

Risselada, H., Verhoef, P. C., & Bijmolt, T. H. (2014). Dynamic effects of social influence and direct marketing on the adoption of high-technology products. *Journal of Marketing, 78*(2), 52-68.

Risselada, H., Verhoef, P. C., & Bijmolt, T. H. (2016). Indicators of opinion leadership in customer networks: self-reports and degree centrality. *Marketing Letters, 27*(3), 449-460.

Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297-318.

Rose, M., & Blodgett, J. G. (2016). Should hotels respond to negative online reviews?. *Cornell Hospitality Quarterly, 57*(4), 396-410.

Rosenbaum, M. S., Otalora, M. L., & Ramírez, G. C. (2017). How to create a realistic customer journey map. *Business Horizons, 60*(1), 143-150.

Rousseau, D. M. (1985). Issues of level in organizational research: Multi-level and cross-level perspectives. *Research in Organizational Behavior, 7*(1), 1-37.

Rude, Stephanie, Eva-Maria Gortner, and James Pennebaker (2004), "Language Use of Depressed and Depression-Vulnerable College Students," *Cognition & Emotion,18* (8), 1121–33.

Rust, R. T., & Cooil, B. (1994). Reliability measures for qualitative data: Theory and implications. *Journal of Marketing Research, 31*(1), 1-14.

Rust, R. T., & Verhoef, P. C. (2005). Optimizing the marketing interventions mix in intermediate-term CRM. *Marketing Science, 24*(3), 477-489.

Rutz, O. J., & Watson, G. F. (2019). Endogeneity and marketing strategy research: an overview. *Journal of the Academy of Marketing Science, 47*(3), 479-498.

Salvato, C. (2009). Capabilities unveiled: The role of ordinary activities in the evolution of product development processes. *Organization Science, 20*(2), 384-409.

Sampson, S. E. (2012). Visualizing service operations. *Journal of Service Research, 15*(2), 182-198.

Sampson, T. D. (2012). Virality: Contagion theory in the age of networks. U of Minnesota Press.

Sandström, S., Edvardsson, B., Kristensson, P., & Magnusson, P. (2008). Value in use through service experience. Managing Service Quality: An International Journal.

Sawhney, M., Verona, G., & Prandelli, E. (2005). Collaborating to create: The Internet as a platform for customer engagement in product innovation. *Journal of Interactive Marketing, 19*(4), 4-17.

Schaefers, T., & Schamari, J. (2016). Service recovery via social media: The social influence effects of virtual presence. *Journal of Service Research, 19*(2), 192-208.

Schiffman, L.G. and L.L. Kanuk (1997), Consumer Behaviour, Sixth Edition. Englewood Cliffs, New Jersey: Prentice-Hall International, Inc.

Schlosser, A. E. (2005). Posting versus lurking: Communicating in a multiple audience context. *Journal of Consumer Research, 32*(2), 260-265.

Schlosser, A. E., White, T. B., & Lloyd, S. M. (2006). Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase Intentions. *Journal of Marketing*, *70*(2), 133-148.

Schmitt , B . H .(2003) Customer Experience Management: A Revolutionary Approach to Connecting with Your Customers. Hoboken, NJ: John Wiley &Sons .

Schmitt, B. (1999). Experiential marketing. *Journal of Marketing Management, 15*(1-3), 53-67.

Schmitt, B. (2011). Experience marketing: Concepts, frameworks and consumer insights. *Foundations and Trends in Marketing, 5*(2), 55-112.

Schmitt, B. H. (2010). *Customer Experience Management: A Revolutionary Approach to Connecting with Your Customers*. John Wiley & Sons.

Schmitt, B., Brakus, J. J., & Zarantonello, L. (2015). From experiential psychology to consumer experience. *Journal of Consumer Psychology, 25*(1), 166-171.

Schmitt, B.H. (2003) Customer Experience Management: A Revolutionary Approach to Connecting With Your Customer. Wiley And Sons, New Jersey.

Schouten, J. W., & McAlexander, J. H. (1995). Subcultures of consumption: An ethnography of the new bikers. *Journal of Consumer Research, 22*(1), 43-61.

Schouten, J. W., McAlexander, J. H., & Koenig, H. F. (2007). Transcendent customer experience and brand community. *Journal of the Academy of Marketing Science, 35*(3), 357-368.

Schweidel, D. A., & Knox, G. (2013). Incorporating Direct Marketing Activity into Latent Attrition Models. *Marketing Science*, *32*(3), 471-487.

Schweidel, D. A., Bradlow, E. T., & Fader, P. S. (2011). Portfolio dynamics for customers of a multiservice provider. *Management Science, 57*(3), 471-486.

Sebastiani, F. (2002). Machine learning in automated text categorization. *ACM Computing Surveys (CSUR), 34*(1), 1-47.

Secomandi, F., & Snelders, D. (2011). The object of service design. *Design Issues, 27*(3), 20-34.

Seibold, D. R., Lemus, D. R., & Kang, P. (2010). Extending the conversational argument coding scheme in studies of argument quality in group deliberations. *Communication Methods and Measures*, *4*(1-2), 46-64.

Seybold, P. B. (2001). Get inside the lives of your customers. *Harvard Business Review, 79*(5), 80-9.

Shah, D., Rust, R. T., Parasuraman, A., Staelin, R., & Day, G. S. (2006). The path to customer centricity. *Journal of Service Research, 9*(2), 113-124.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research, 15*(3), 325-343.

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science*, *22*(11), 1391-1396.

Sheth, J. N., & Parvatiyar, A. (1995). The Evolution of Relationship Marketing. *International Business Review*, *4*(4), 397-418.

Shostack, G. L. (1985). The service encounter. *Planning the Service Encounter*, 243-254.

Singh, P. V., Tan, Y., & Youn, N. (2011). A Hidden Markov Model of Developer Learning Dynamics in Open Source Software Projects. *Information Systems Research*, *22*(4), 790-807.

Skiera, B., & Abou Nabout, N. (2013). Practice prize paper—PROSAD: A bidding decision support system for profit optimizing search engine advertising. *Marketing Science, 32*(2), 213-220.

Smith, A. K., Bolton, R. N., & Wagner, J. (1999). A model of customer satisfaction with service encounters involving failure and recovery. *Journal of Marketing Research, 36*(3), 356-372.

Smith, S., & Wheeler, J. (2002). Managing the customer experience: Turning customers into advocates. Pearson Education.

Solomon, M. R. (1983). The role of products as social stimuli: A symbolic interactionism perspective. *Journal of Consumer Research, 10*(3), 319-329.

State of Marketing, Salesforce Marketing Cloud https://www.salesforce.com/form/pdf/5th-state-of-marketing/

Steuer, J. (1992). Defining Virtual Reality: Dimensions Determining

Telepresence. *Journal of Communication*, *42*(4), 73-93.

Sundaram, D. S., Kaushik Mitra, and Cynthia Webster (1998), ‘‘Word-of-Mouth Communications: A Motivational Analysis,’’ Advances in Consumer Research, 25, 527-531.

Sunder, S., Kim, K. H., & Yorkston, E. A. (2019). What Drives Herding Behavior in Online Ratings? The Role of Rater Experience, Product Portfolio, and Diverging Opinions. *Journal of Marketing*, *83*(6), 93-112.

Swaid, S. I., & Wigand, R. T. (2009). Measuring the quality of e-service: Scale development and initial validation. *Journal of Electronic Commerce Research, 10*(1), 13-28.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24-54.

Tax, S. S., & Brown, S. W. (1998). Recovering and learning from service failure. *Sloan Management Review*, *40*(1), 75-88.

Tax, S. S., McCutcheon, D., & Wilkinson, I. F. (2013). The service delivery network (SDN) a customer-centric perspective of the customer journey. *Journal of Service Research, 16*(4), 454-470.

Teixeira, J., Patrício, L., Nóbrega, L., Constantine, L., & Fisk, R. P. (2012). Designing Services with Model-based Methods. In proceedings of the 19th International Product Development Management Conference.

Temkin, B., & Bliss, J. (2011). Customer Experience Overview. *Journal of Retailing, 43*(4), 50-62.

Tirunillai, S., & Tellis, G. J. (2012). Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science, 31*(2), 198-215.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of Marketing Research, 51*(4), 463-479.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

Travis E Oliphant. 2007. SciPy: Open source scientific tools for Python. Computing in Science and Engineering 9: 10–20. http://doi.org/10.1109/MCSE.2007.58

Van Doorn, J., & Verhoef, P. C. (2008). Critical incidents and the impact of satisfaction on customer share. *Journal of Marketing, 72*(4), 123-142.

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of Service Research, 13*(3), 253-266.

Van Nierop, J. E., Leeflang, P. S., Teerling, M. L., & Huizingh, K. E. (2011). The impact of the introduction and use of an informational website on offline customer buying behavior. *International Journal of Research in Marketing, 28*(2), 155-165.

Van Noort, G., & Willemsen, L. M. (2012). Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms. *Journal of Interactive Marketing, 26*(3), 131-140.

Van Vaerenbergh, Y., Varga, D., De Keyser, A., & Orsingher, C. (2019). The service recovery journey: Conceptualization, integration, and directions for future research. *Journal of Service Research, 22*(2), 103-119.

Vargo, S. L., & Lusch, R. F. (2004). The four service marketing myths: remnants of a goods-based, manufacturing model. *Journal of Service Research, 6*(4), 324-335.

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: continuing the evolution. *Journal of the Academy of Marketing Science, 36*(1), 1-10.

Vargo, S. L., Maglio, P. P., & Akaka, M. A. (2008). On value and value co-creation: A service systems and service logic perspective. *European Management Journal, 26*(3), 145-152.

Venkatesan, R., Kumar, V., & Ravishanker, N. (2007). Multichannel shopping: causes and consequences. *Journal of Marketing, 71*(2), 114-132.

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From multi-channel retailing to omni-channel retailing: introduction to the special issue on multi-channel retailing. *Journal of Retailing, 91*(2), 174-181.

Verhoef, P. C., Kooge, E., & Walk, N. (2016). Creating value with big data analytics: Making smarter marketing decisions. Routledge.

Verhoef, P. C., Kooge, E., & Walk, N. (2016). Creating value with big data analytics: Making smarter marketing decisions. New York: Routledge.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. *Journal of Retailing, 85*(1), 31-41.

Verhoef, P. C., Neslin, S. A., & Vroomen, B. (2007). Multichannel customer management: Understanding the research-shopper phenomenon. International *Journal of Research in Marketing, 24*(2), 129-148.

Verhoef, P. C., Reinartz, W. J., & Krafft, M. (2010). Customer engagement as a new perspective in customer management. *Journal of Service Research, 13*(3), 247-252.

Verleye, Katrien (2015), "The Co-Creation Experience from the Customer Perspective: Its Measurement and Determinants," *Journal of Service Management, 26*(2), 321-342.

Vermunt, J. K., & Magidson, J. (2015). Upgrade manual for Latent GOLD 5.1. *Belmont, MA: Statistical Innovations*.

Villas-Boas, J. M., & Winer, R. S. (1999). Endogeneity in brand choice models. *Management Science, 45*(10), 1324-1338.

Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice, 20*(2), 122-146.

Voorhees, C. M., Fombelle, P. W., Gregoire, Y., Bone, S., Gustafsson, A., Sousa, R., & Walkowiak, T. (2017). Service encounters, experiences and the customer journey: Defining the field and a call to expand our lens. *Journal of Business Research, 79*(C), 269-280.

Walls, A. R., Okumus, F., Wang, Y. R., & Kwun, D. J. W. (2011). An epistemological view of consumer experiences. *International Journal of Hospitality Management, 30*(1), 10-21.

Walls, A. R., Okumus, F., Wang, Y. R., & Kwun, D. J. W. (2011). An Epistemological View of Consumer Experiences. *International Journal of Hospitality Management*, *30*(1), 10-21.

Wang, R. J. H., Malthouse, E. C., & Krishnamurthi, L. (2015). On the go: How mobile shopping affects customer purchase behavior. *Journal of Retailing, 91*(2), 217-234.

Wang, Y., & Chaudhry, A. (2018). When and how managers' responses to online reviews affect subsequent reviews. *Journal of Marketing Research, 55*(2), 163-177.

Webster Jr, F. E., & Wind, Y. (1972). A General Model for Understanding Organizational Buying Behavior. *Journal of Marketing*, *36*(2), 12-19.

Webster, F. E., & Lusch, R. F. (2013). Elevating marketing: marketing is dead! Long live marketing!. *Journal of the Academy of Marketing Science, 41*(4), 389-399.

Wedel, M., Kamakura, W., Arora, N., Bemmaor, A., Chiang, J., Elrod, T., ... & Poulsen, C. S. (1999). Discrete And Continuous Representations of Unobserved Heterogeneity in Choice Modeling. *Marketing Letters*, *10*(3), 219-232.

Weitzl, W., & Hutzinger, C. (2017). The effects of marketer-and advocate-initiated online service recovery responses on silent bystanders. *Journal of Business Research, 80*(C), 164-175.

Wentura, D., & Greve, W. (2005). Assessing The Structure of Self-Concept: Evidence for Self-Defensive Processes by Using A Sentence Priming Task. *Self and Identity*, *4*(3), 193-211.

Wertheimer, E. F. (1945). The International Secretariat: A Great Experiment in International Administration (No. 3). Carnegie endowment for international peace.

Wertheimer, M. (1945), Productive Thinking. New York: Harper & Row

Westbrook, R. A. (1987). Product/Consumption-Based Affective Responses and Postpurchase Processes. *Journal of Marketing Research*, *24*(3), 258-270.

Westbrook, R. A., & Oliver, R. L. (1991). The Dimensionality of Consumption Emotion Patterns and Consumer Satisfaction. *Journal of Consumer Research*, *18*(1), 84-91.

Winsted, K. F. (1997). The service experience in two cultures: A behavioral perspective.

Journal of Retailing, 73(3), 337-360.

Witell, L., Kristensson, P., Gustafsson, A., & Löfgren, M. (2011). Idea Generation: Customer Co-Creation Versus Traditional Market Research Techniques. *Journal of Service Management*, *22*(2), 140-159.

Wojnicki, A. C., & Godes, D. (2008). Word of Mouth as Selfenhancement, HBS Marketing Research Paper No. 06-01. *Boston, MA: Harvard Business School Marketing Unit*.

Xia, L. (2013). Effects of companies' responses to consumer criticism in social media. *International Journal of Electronic Commerce, 17*(4), 73-100.

Xie, C., Bagozzi, R. P., & Troye, S. V. (2008). Trying to prosume: toward a theory of consumers as co-creators of value. *Journal of the Academy of Marketing Science, 36*(1), 109-122.

Xie, K. L., & Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. *International Journal of Hospitality Management*, *67*, 174-184.

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, *43*, 1-12.

Yan, L., & Tan, Y. (2014). Feeling Blue? Go Online: An Empirical Study of Social Support among Patients. *Information Systems Research*, *25*(4), 690-709.

Ye, F., Zhang, L., & Li, Y. (2018). Strategic choice of sales channel and business model for the hotel supply chain. *Journal of Retailing*, *94*(1), 33-44.

Ye, Q., Gu, B., Chen, W., & Law, Rob, (2008). Measuring the value of managerial responses to online reviews - A natural experiment of two online travel agencies.

ICIS 2008 Proceedings. Paper 115.

Zaltman, G., & Zaltman, L. H. (2008). *Marketing Metaphoria: What Deep Metaphors Reveal About the Minds Of Consumers*. Harvard Business Press.

Zarantonello, L., Jedidi, K., & Schmitt, B. H. (2013). Functional and experiential routes to persuasion: An analysis of advertising in emerging versus developed markets. *International Journal of Research in Marketing*, *30*(1), 46-56.

Zervas, G., Proserpio, D., & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average. *Where Every Stay is Above Average (January 28, 2015)*.

Zhang, J. Z., Netzer, O., & Ansari, A. (2014). Dynamic targeted pricing in B2B relationships. *Marketing Science, 33*(3), 317-337

Zhang, J. Z., Watson Iv, G. F., Palmatier, R. W., & Dant, R. P. (2016). Dynamic relationship marketing. *Journal of Marketing, 80*(5), 53-75.

Zhu, Z., Nakata, C., Sivakumar, K., & Grewal, D. (2013). Fix it or leave it? Customer recovery from self-service technology failures. *Journal of Retailing, 89*(1), 15-29.

Ziegler, C. N., Skubacz, M., & Viermetz, M. (2008, December). Mining and Exploring Unstructured Customer Feedback Data Using Language Models and Treemap Visualizations. In *2008 IEEE/WIC/ACM International Conference On Web Intelligence and Intelligent Agent Technology* (Vol. 1, Pp. 932-937). IEEE.

Zomerdijk, L. G., & Voss, C. A. (2010). Service design for experience-centric services. *Journal of Service Research, 13*(1), 67-82.

Zomerdijk, L. G., & Voss, C. A. (2011). NSD processes and practices in experiential services. *Journal of Product Innovation Management, 28*(1), 63-80.